Title

Climate Change Adaptation and Resilience Building: Funding Gaps, Political Biases, and Empirical Insights into Mitigation Strategies

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Climate Change Adaptation and Resilience Building: Funding Gaps, Political Biases, and Empirical Insights into Mitigation Strategies

A dissertation submitted in partial satisfaction
of the requirements for the degree

Doctor of Philosophy
in
Environmental Science and Management

by

Gabriela Jazmín Alberola Espino

Committee in charge:

Professor Mark Buntaine, Chair
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Professor Paasha Mahdavi
Professor Sarah Anderson

September 2024

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Climate Change Adaptation and Resilience Building: Funding Gaps, Political Biases, and Empirical Insights into Mitigation Strategies

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Gabriela Jazmín Alberola Espino

A mamá Elma y papá José, por darme alas y por siempre brindarme un lugar seguro al cual regresar

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Curriculum Vitæ
Gabriela Jazmín Alberola Espino

SUMMARY OF QUALIFICATIONS

- Interdisciplinary background with a focus on environmental science and management, political science, political economy, and climate finance.
- Twelve years of project management experience honed through the development of science programs in higher education and consultancy work.
- Eleven years of leadership experience mentoring STEM students.
- Demonstrated ability to facilitate communications and produce results in multi-stakeholder projects.
- Twelve years of experience conducting data-driven analysis in R, Python, ArcGIS, Excel, and MS Access.
- Multicultural contributor. Bilingual in English and Spanish.

EDUCATION

PhD in Environmental Science and Management — Sep. 2018 - Sep. 2024
UC Santa Barbara — *GPA: 3.94*

Master of Arts in Political Science — Sep. 2018 - Sep. 2020
UC Santa Barbara — *GPA: 3.92*

Master of Science in Coastal and Watershed Sci. and Policy — Aug. 2010 - May 2012
CSU Monterey Bay — *GPA: 3.92*

Bachelor of Science in Environmental Biology — March 2000 - May 2006
Universidad de Panamá, Panama City, Panama — *GPA: 3.15*

PROFESSIONAL EXPERIENCE

Consultant — UN Women — *May 2023 - Nov. 2023*
Remote

- Lead quantitative and qualitative research on climate finance, gender, and conflict topics.
- Conduct quantitative analyses of global climate finance commitments.

- Conduct country case studies in Bosnia and Herzegovina, Guatemala, and Haiti.
- Co-author a final public-facing report.

Teaching Assistant — Global Studies and Political Science *Sep. 2019 - June 2022*
UC Santa Barbara, Santa Barbara, CA

- Led 3 weekly discussion sections for 20 students.
- Designed and delivered course materials on globalization, political science, and political economy.
- Managed a team of 4 teaching assistants, coordinating tasks and acting as a liaison.
- Provided one-on-one student support for lessons, feedback, and mentorship.

Graduate Researcher — Buntaine Lab; ENVENT Lab *Sep. 2018 - Sep. 2024*
UC Santa Barbara, Santa Barbara, CA

- Conduct research on environmental violence, including design and deployment of survey experiments, conduct interviews, and collect and analyze observational data.
- Establish collaborative research relationships with international partners in Latin America.
- Develop mechanisms to assess climate change adaptation projects using remote sensing, GIS, interviews, and quantitative analyses.
- Mentor a team of 11 undergraduate researchers.

Student Services Coordinator — College of Science *Aug. 2014 - Aug. 2018*
CSU Monterey Bay, Monterey Bay, CA

- Developed and implemented student outreach and retention strategies with a strong focus on diversity, career development, professional development, and student wellbeing.
- Mentored graduate and undergraduate science students in academic and career topics.
- Created and delivered professional development curriculum for science majors.
- Researched, applied to, and managed grants for STEM student success programs.
- Created data management protocols and systems to increase efficiency.

Research Coordinator — Ag. and Natural Resources Lab *March 2013 - Aug. 2014*
CSU Monterey Bay, Monterey Bay, CA

- Guided, coordinated, and advised graduate and undergraduate research projects in water quality, bacterial bioremediation, and greenhouse gas emissions.
- Provided support to students by monitoring the development of their research projects, maintaining project records, and directing them to resources and services.
- Developed data entry, data sharing, and data storage systems to improve efficiency and data security.

- Prepared technical and non-technical reports for project partners and other stakeholders.

Spanish – English Interpreter and Translator — Freelancer *Oct. 2009 - Aug. 2014*
Monterey, CA

- Provided on-site, over the phone, and video interpretation and translation services for Medical, Environmental, Insurance, Finance, and Customer Service fields.

Outreach Coordinator — Planning & Cons. League Foundation *June 2011 - Dec. 2012*
Monterey, CA

- Prepared, distributed, and presented Spanish and English project materials to support outreach efforts.
- Provided logistic support for stakeholder decision-making processes.
- Assisted and provided support to the Carmel River Task Force.

Staff writer — Carmel River Watershed Conservancy *Dec. 2011 - Dec. 2012*
Monterey, CA

- Developed a database of all the active projects in the Carmel River Watershed.
- Prepared detailed maps and reports to inform the management of the watershed.
- Spearheaded efforts to review and update the Carmel River Watershed Action Plan.
- Wrote articles for the organization's newsletters and website.
- Managed the organization's website.

COMMUNITY ENGAGEMENT

- Reviewer for the National Institute of Food and Agriculture competitive grants application. 2017 - Present.
- Board of Directors, Carmel River Watershed Conservancy. 2015 - 2018.
- Board of Directors, Sustainability Academy of Monterey. 2016 - 2018.

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- Switzer Fellow. The Robert and Patricia Switzer Foundation. 2021.
- Environmental Fellow. Environmental Fellows Program at the Yale School of the Environment. 2021.
- E. Kika De La Garza Fellow. USDA. 2017.

WORKS IN PROGRESS

Academic Papers:

- Alberola, G. (2024). Uncovering the Exposure Gap: Rethinking Vulnerability Targeting in Climate Change Adaptation Funding.
- Alberola, G., & Buntaine, M. (2024). Aligned Mayors Receive More Climate Funds: The Partisan Politics of Adaptation.
- Alberola, G., & Mildenberger, M. (2024). Public Attitudes Towards the Use of Violence Against Activists in Environmental Conflicts.
- Alberola, G., & Buntaine, M. (2024). Resilience Curves and the Political Economy of Climate Adaptation.

Reports:

- Alberola, G., & Carlitz, R. (2023, in publication). Gender-Responsive Approaches in Climate Finance: A Study in Conflict-Affected and Fragile Contexts. Report for UN Women.

CONFERENCES AND SEMINARS

- Conference on The Political Economy of Climate and the Environment, Los Angeles, August 30, 2023.
- Duck Family Graduate Workshop in Environmental Politics and Governance, Seattle, May 10-12, 2023.
- Midwest Political Science Association (MPSA) Annual Conference, Chicago, April 13-16, 2023.
- Bren School's PhD Symposium 2023, Santa Barbara, March 3, 2023.
- Bren School's PhD Symposium 2022, Santa Barbara, February 25, 2022.
- Sustainability and Development Conference, Online, January 24-28, 2022.
- Environmental Grantmakers Association (EGA), Online, October 5-7, 2021.
- Environmental Politics and Governance Conference (EPG), Online, June 23-25, 2021.
- Bren School's Environmental Justice Symposium, Online, May 20-21, 2021.

Abstract

Climate Change Adaptation and Resilience Building: Funding Gaps, Political Biases, and Empirical Insights into Mitigation Strategies

by

Gabriela Jazmín Alberola Espino

My thesis explores three interconnected areas related to climate change: vulnerability, the equitable distribution of adaptation resources, and resilience building. In the first two chapters, I examine the flow of funding from international climate organizations to municipalities in Central America and the Caribbean. I explore the role that clientelism plays in the allocation of adaptation funds at the municipal level and assess whether the most vulnerable communities are receiving the funds they need. In my third chapter, I evaluate which types of social vulnerabilities, experiences, and interventions predict impacts and recovery from hurricanes. Overall, I find that political clientelism diverts funds away from truly vulnerable areas, that subnational targeting needs to incorporate more comprehensive and intersectional approaches to climate vulnerability, and that even under favorable conditions, resilience building remains elusive for disaster-prone communities.

Contents

Chapter 1

Uncovering the Exposure Gap: Rethinking Vulnerability Targeting in Climate Change Adaptation Funding

Abstract: Using both established and novel measures of local adaptive capacity, sensitivity, and climate change exposure, this study evaluates whether international adaptation funding is flowing to the most climate vulnerable areas subnationally. The study examines the distribution of twelve climate finance funds to 1,358 municipalities across seven countries in Central America and the Caribbean, spanning the years 2007 to 2022. I find that while adaptive capacity and sensitivity are both significant predictors of higher funding for adaptation from international donors, future exposure to climate change does not seem to play a role in the allocation of funds. This finding highlights a critical blind spot in the allocation of adaptation funding. Without the consideration of future exposure to climate change, the most climate-vulnerable communities—those at the intersection of adaptive capacity, sensitivity, and exposure—are at risk of being overlooked. This is the first study

to systematically track subnational climate adaptation funding across multiple organizations, countries, and years and evaluate the relationship between allocations and individual components of climate change vulnerability.

1.1 Introduction

Vulnerability is a fundamental guiding principle for the allocation of international climate assistance. The concept of prioritizing the most vulnerable is enshrined in the UN Framework Convention on Climate Change (UNFCCC), wherein developed country Parties agreed to assist "particularly vulnerable" developing countries in meeting their adaptation needs (1). This principle was reaffirmed in the 2009 Copenhagen Accord, wherein developed country Parties pledged USD 100 billion annually for climate strategies in developing countries, emphasizing the need to prioritize the most vulnerable among them, such as the least developed countries and the small island developing states (2; 3).

Vulnerability to climate change arises from the interplay of social and physical factors, broadly grouped into three categories: adaptive capacity, sensitivity, and exposure (4; 5; 6). Adaptive capacity refers to a system's resources, capabilities, and institutions that enable adaptation to climate change; sensitivity refers to the degree to which a system can be affected by climate-related stimuli; and exposure denotes the extent to which a system experiences climatic changes. While several indices have been developed to assess vulnerability at the country level, the use of subnational vulnerability maps and indices to identify vulnerable areas within countries is not widespread yet (7; 8).

While the UNFCCC and subsequent climate agreements consistently emphasize the importance of prioritizing the allocation of climate financing based on vulnerability needs, the focus has remained on country-level vulnerability (9; 10). To date, limited attention and systematic research have focused on describing or explaining the subnational distribution of international climate adaptation funding in developing countries (11; 12).

Furthermore, while climate financing organizations disclose recipient countries and amounts, information about the final subnational distribution of those funds is not consistently recorded nor disclosed (11). The absence of subnational vulnerability maps, coupled with the absence of subnational adaptation allocation data, presents a challenge when attempting to determine whether vulnerable communities are receiving the necessary priority in funding allocation. Despite more than three decades of international climate financing mobilization, a clear understanding of the subnational distribution of adaptation efforts and the efficacy of need-based targeting remains elusive. To date, this study represents the most comprehensive evaluation of subnational vulnerability-based targeting of international adaptation aid, examining multiple countries, twelve different funds, and a period of fifteen years.

Central America and the Caribbean emerge as a particularly relevant region for studying the relationship between subnational vulnerability to climate change and the allocation of international climate funds. This stems from several factors, including the heightened climate vulnerability of the region (13), its substantial need for international assistance to address climate change (14), and the explicit commitment of its nations to prioritize vulnerable populations, as stated in their Nationally Determined Contributions (NDCs), regional adaptation plans, and national climate change legislation [1].

This region has been categorized as being at substantial risk and is already experiencing the negative impacts of global climate change, such as record-breaking temperatures, reduced rainfall, and intensified storms (13). With over 50 million people in this region, nearly 45% of them living in poverty [2], understanding the subnational distribution of climate funds and evaluating the prioritization of funding for the most vulnerable areas is essential. The exclusive focus of international climate funds on vulnerable countries, without systematically targeting

[1] Based on the author's review of Nationally Determined Contributions (NDCs), regional adaptation plans, and national climate change legislation for all the countries in the study

[2] 2014 data from ECLAC's CEPALSTAT database (CEPALSTAT) and The World Bank DataBank (DataBank).

the most susceptible areas within them, risks overlooking subregions that are disproportionately affected by climate change.

In this study, I find that the two aspects of climate change vulnerability associated with socioeconomic factors —adaptive capacity and sensitivity—are significant predictors of increased adaptation funding. Conversely, future exposure to climate change does not predict fund allocation. This finding suggests that international climate funds might be overlooking the areas most at risk from climate change, specifically those at the intersection of low adaptive capacity, high sensitivity, and high exposure. This oversight represents a critical gap in the distribution of adaptation funding and underscores the need for climate financing organizations to improve vulnerability-based targeting strategies. An essential first step is enhancing the transparency and accessibility of data on fund recipients at the subnational level. Remarkably, none of the organizations in the sample (Table 1.1) disclosed their subnational fund distribution consistently. To ensure that climate aid reaches the communities most in need, it is essential to adopt a more transparent and accurate approach to subnational fund tracking. This should be coupled with a holistic prioritization strategy that considers overall vulnerability beyond only socioeconomic factors.

1.2 Results

1.2.1 Mapping subnational climate aid allocations

I find wide variation in the distribution of climate adaptation aid at the municipal level in the seven countries of Central America and the Caribbean that were analyzed –Panama, Costa Rica, the Dominican Republic, Nicaragua, Honduras, El Salvador, and Guatemala– (Figure 1.1). These maps provide the first snapshot of climate adaptation funding at the subnational level that simultaneously captures multiple funds and multiple countries over multiple years.

Figure 1.a shows the distribution of funds in current USD and Figure 1.b shows the distribution of funds in project counts.

This analysis involved tracking the allocation of climate adaptation projects from 2007 to 2020 from multiple climate financing organizations. Among the 35 climate funds active in the region, only twelve of them funded location-specific climate adaptation projects in the countries in the sample. These twelve funds funded 191 unique adaptation projects during the study period, cumulatively valued at $2,091,114,406 (current USD). Of those 191 projects, I geolocated 87 to the municipal level, collectively amounting to $660,424,579 (current USD) in funding and impacting 817 municipalities. The remaining projects, about 50% of the original list of 191 projects, could not be traced to the level of municipality based on the documentation provided by the funding organizations, which means that they could not be accurately tracked to assess whether they are effectively targeted towards the more vulnerable areas. This lack of traceability remains a considerable challenge in evaluating the efficacy and focus of climate adaptation funding subnationally.

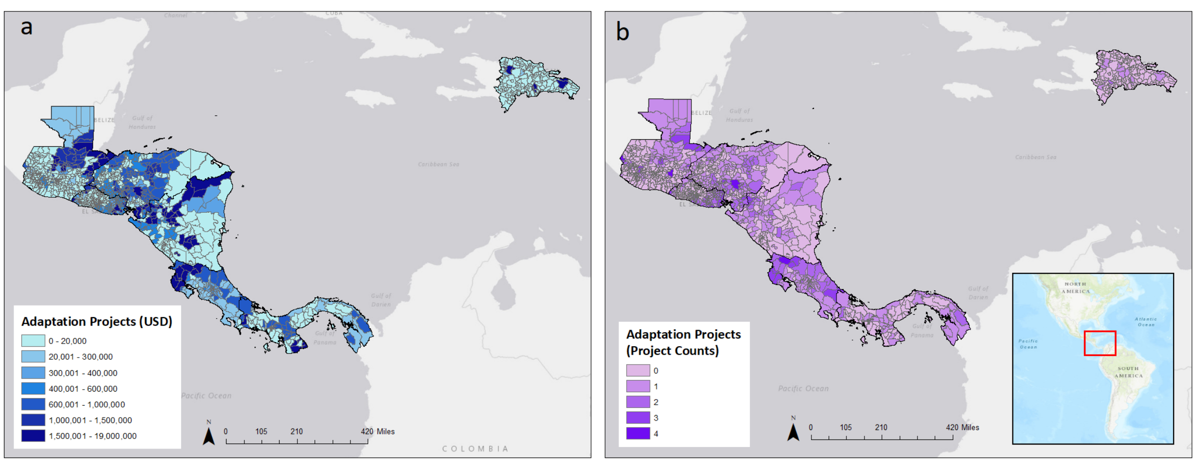

Figure 1.1: Distribution of projects at the municipal level, shown as total investments in USD (1.a) and total project counts (1.b), from 12 different climate finance funds over the period 2007–2022

1.2.2 Mapping subnational vulnerability

The maps displayed in Figure 1.2 highlight the extensive variation in vulnerability levels among different municipalities. These variations are shown across the three key categories of climate change vulnerability: adaptive capacity (panel a), sensitivity (panel b), and exposure (panel c). The map in panel d shows a composite vulnerability index that combines the three vulnerability categories.

I developed these municipality-level vulnerability indices drawing upon established methodologies for evaluating adaptive capacity, sensitivity, and exposure to climate change (4; 7). The data sources and indicators used are listed in Table 1.2 and described in more detail in the Methods section. The climate change exposure index is based on climate projections for the Shared Socioeconomic Pathway (SSP) scenario 5, using data from 23 General Circulation models from the WorldClim database for the period between 2021-2040. It assesses vulnerability through three indicators: maximum temperature of the warmest month (°C), minimum temperature of the coldest month (°C), and annual precipitation (mm). The adaptive capacity vulnerability index comprises four indicators related to adaptive capacity: access to water, access to electricity, access to sanitary toilets, and percentage of adults with only primary education or less. The sensitivity index focuses on three sensitivity indicators: dependency ratio, percentage of minority population, and experience of past disasters. All three indices are standardized using z-scores, where each unit represents one standard deviation away from the mean. In all three indices, higher scores indicate greater vulnerability to climate-related challenges.

It is important to note that the selection of indicators and data sources shapes the development of vulnerability indices, and that uncertainty is intrinsic to their creation. The indices used in this study offer a thorough assessment grounded in the current understanding of local adaptive capacity, sensitivity, and exposure, drawing on a comprehensive array of indicators. However, while these indices serve as a valuable baseline to understand vulnerability at a macro

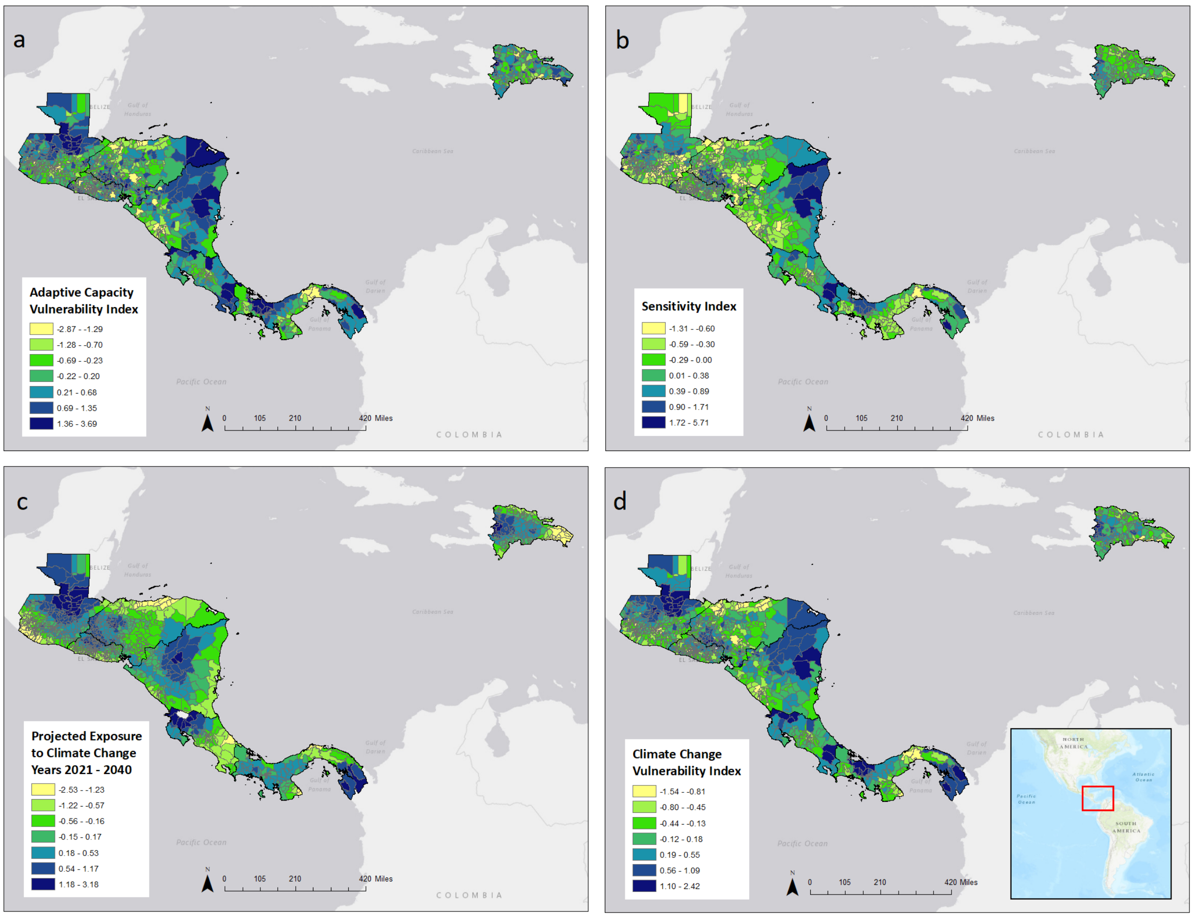

Figure 1.2: Distribution of climate change vulnerability, as disaggregated components of adaptive capacity (panel a), sensitivity (panel b), and climate change exposure (panel c), and as a single index that combines the 3 categories (panel d). For all indices, higher values indicate higher vulnerability.

level, practitioners are encouraged to complement them with local analyses, data, and expertise from regional specialists.

1.2.3 Low adaptive capacity and high sensitivity predict higher adaptation funding

I find that adaptive capacity is highly predictive of climate adaptation allocations at the municipal level, in both the aggregated analysis of all allocations over time (cross-sectional analysis, Models 1 and 2) and in the more granular examination of year-to-year allocations (panel analysis, Models 3 and 4) (Figure 1.3 below; Table A.1 in Appendix A). A one-unit increase in the adaptive capacity vulnerability index, moving from less vulnerable to more vulnerable, predicts, on average, a 212.64% [3] increase (95% confidence interval: 19.18% to 720.11%, $\alpha < 0.05$) in adaptation allocations and a 0.14 increase (95% confidence interval: 0.05 to 0.23, $\alpha < 0.01$) in project counts over the entire time span of the study in the cross-sectional models 1 and 2. A one-unit increase in the adaptive capacity vulnerability index also predicts, on average, a 13.85% (95% confidence interval: 8.05% to 19.97%, $\alpha < 0.001$) increase in adaptation allocations and a 0.01 increase (95% confidence interval: 0.005 to 0.013,$\alpha < 0.001$) in project counts from one year to the next in the panel models 3 and 4. The cross-sectional analysis offers a consolidated "snapshot," showing that higher vulnerability correlates with increased allocations, based on aggregated values in fifteen years of data. In contrast, the panel analysis provides a detailed, year-to-year perspective, describing how allocations may fluctuate annually, on average, in correlation with variations in vulnerability at the municipal level.

Although sensitivity to climate change initially appears non-predictive in most of the models in Figure 1.3, its predictive capacity for funding from international donors emerges in 'leave-one-out' robustness analyses where one variable is excluded at a time to re-evaluate

[3] Because the scale is logarithmic, this values is calculated as $(1-e^{B})*100$, e.g., $(1-e^{1.140})*100 = 212.64\%$.

the model (Tables A.3 to A.6 in Appendix A). This can be attributed to the overlapping nature of adaptive capacity and sensitivity, as both are based on socioeconomic vulnerability metrics that are closely correlated. Consequently, when both variables are included in a single model, adaptive capacity emerges as the more dominant predictor. However, sensitivity also holds predictive significance when examined independently. Exposure, nonetheless, remains non-predictive of allocations when adaptive capacity and sensitivity are excluded from the models.

1.2.4 Exposure to climate change does not predict higher adaptation funding

While low adaptive capacity and high sensitivity to climate change do seem to be linked to higher adaptation allocations, exposure is not predictive of allocations in any of the models (Figure 1.3 below; Tables A.1 to A.6 in Appendix A). This finding persists in interactive models, where allocations are modeled as a function of adaptive capacity x sensitivity x exposure. Marginal effects plots shown in Figures 1.4 to 1.7 detail variations in predicted adaptation funding when holding one predictor variable at its mean value and varying the two others. Figure 1.4 shows the results from model 1, which uses the cross-sectional version of the data and allocations are presented in current USD; Figure 1.5 shows the results from model 2, which uses the cross-sectional version of the data and allocations are presented in project counts; Figure 1.6 shows the results from model 3, which uses the panel version of the data and allocations are presented in current USD; and Figure 1.7 shows the results from model 4, which uses the panel version of the data and allocations are presented in project counts. Although there are minor variations in predicted funding when considering different levels of adaptive capacity and exposure, as well as sensitivity and exposure, these variations are not statistically significant. This suggests that locations with low adaptive capacity combined with high sensitivity or exposure are not associated with increased allocations due to the presence of multiple vulnerabilities

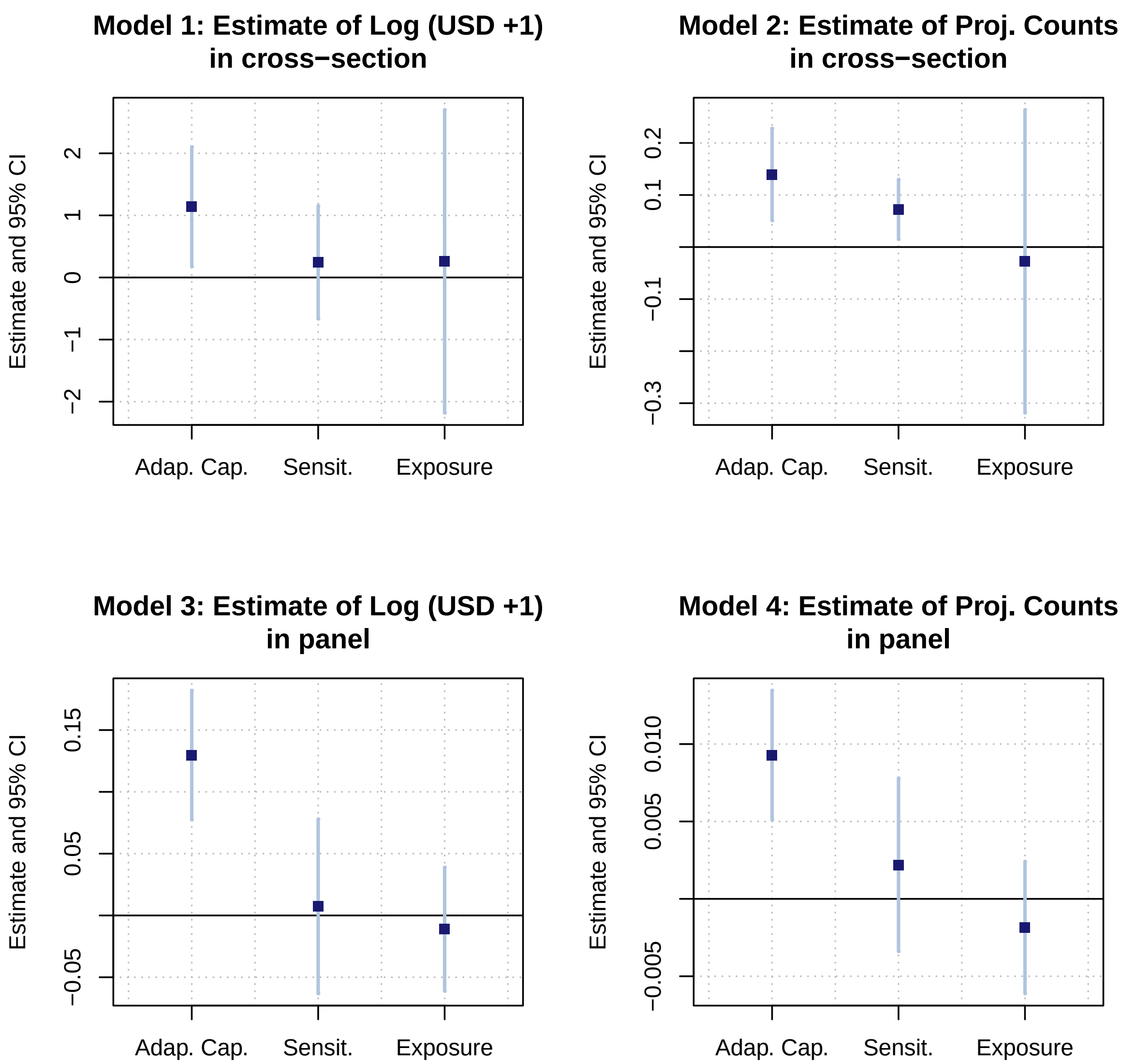

Figure 1.3: Estimates and 95% Confidence Intervals for Base Models 1-4, where allocation of adaptation funds are modeled as a function of adaptive capacity + sensitivity + exposure. Adaptive capacity consistently predicts allocation across all models. Although not apparent in these coefficient plots, sensitivity is also predictive of allocations when adaptive capacity is excluded from the model (please see leave-one-out analyses in section A.2 of Appendix A for additional information).

simultaneously. This pattern remains consistent across two additional measures of exposure, sea level rise and alternative global circulation models, which are detailed in Appendix A. The results of the interactive models are also presented in table format in the Appendix A.

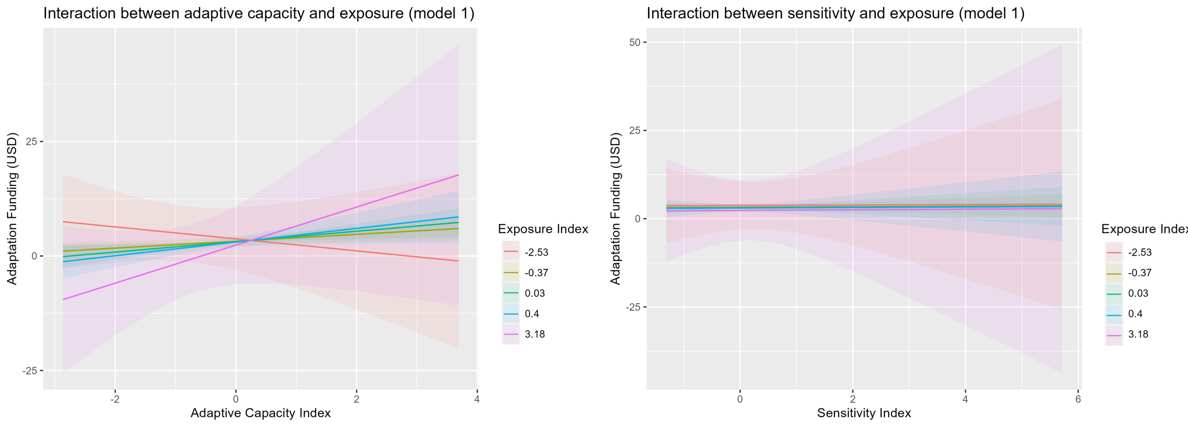

Figure 1.4: In Interactive Model 1, which uses cross-sectional data and models allocations in current USD, we observe no statistically significant interaction between exposure and adaptive capacity (left panel) or between exposure and sensitivity (right panel).

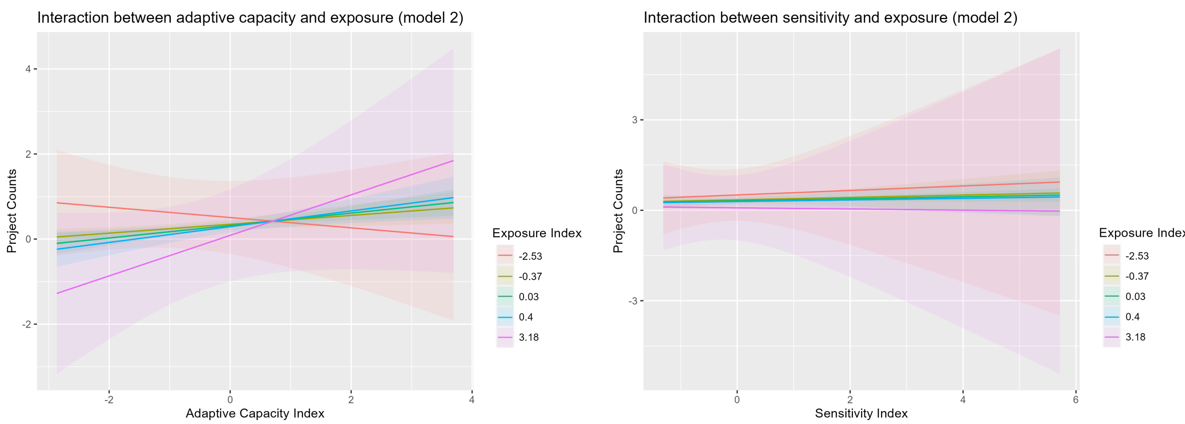

Figure 1.5: In Interactive Model 2, which uses cross-sectional data and models allocations in project counts, we observe no statistically significant interaction between exposure and adaptive capacity (left panel) or between exposure and sensitivity (right panel).

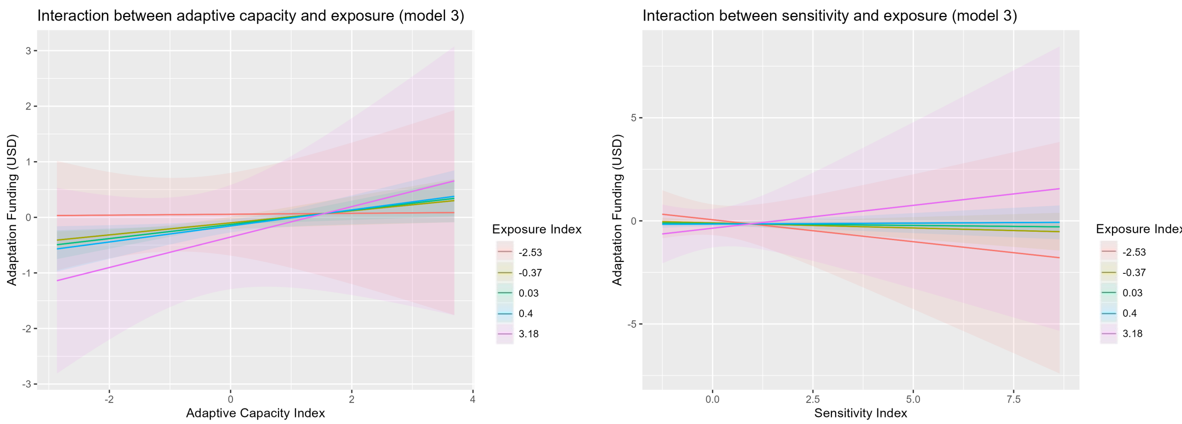

Figure 1.6: In Interactive Model 3, which uses panel data and models allocations in current USD, we observe no statistically significant interaction between exposure and adaptive capacity (left panel) or between exposure and sensitivity (right panel).

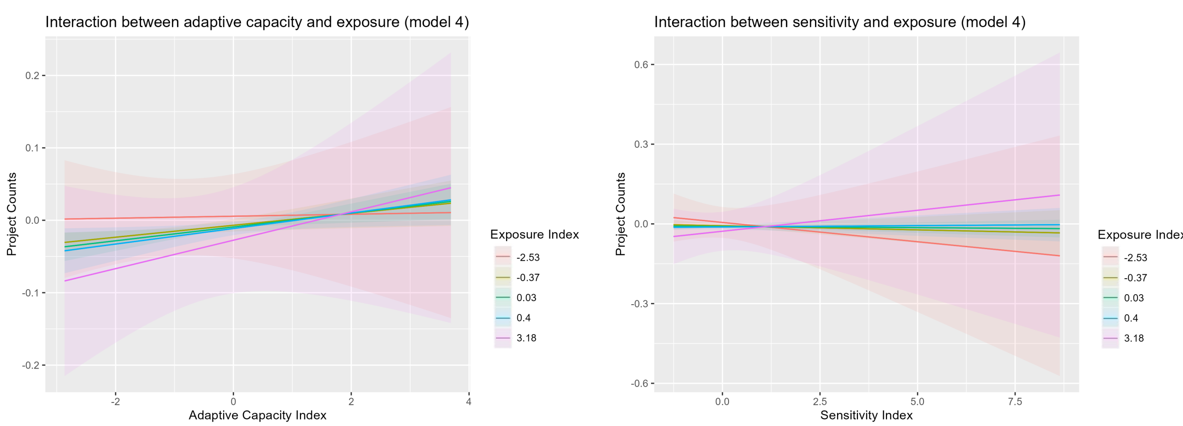

Figure 1.7: In Interactive Model 4, which uses panel data and models allocations in project counts, we observe no statistically significant interaction between exposure and adaptive capacity (left panel) or between exposure and sensitivity (right panel).

1.3 Discussion and Conclusion

I find that adaptive capacity and sensitivity, two of the three components of climate change vulnerability, are significant predictors of municipal-level climate adaptation funding. In contrast, exposure to climate change neither independently predicts higher funding nor does it in combination with the other two components. These findings suggest that donors and recipients may not be prioritizing funding allocations based on comprehensive or intersectional understandings of climate change vulnerability that take into account exposure, but more on established understandings of socioeconomic vulnerability alone. This finding is consistent with recent work by Alcañiz and Giraudy (2023)(11) which finds that "green" funding organizations tend to target poorer areas within countries.

Climate adaptation efforts, which are distinct from traditional development aid and poverty alleviation, require a more holistic approach to subnational allocations based on intersectional climate risks. Understanding the interactions among different components of climate change vulnerability is crucial for efficient adaptation aid prioritization. Therefore, this research advocates for a reevaluation of vulnerability considerations in climate finance allocation strategies, emphasizing the need to address intersectional vulnerabilities within countries.

This study should be carefully interpreted because of two main factors. First, the adaptation project dataset analyzed covers only about 50% of location-specific adaptation projects in the sample countries. While the omitted projects are not expected to be systematically different from the projects analyzed here, the inability to evaluate a larger dataset is suboptimal. The second limitation of this research is the lack of time-varying data for some of the indicators that make up the climate vulnerability indices. Most of the countries in the region have not updated their census in over a decade, leading to a reliance on data from the 2010 censuses alone. Because adaptation capacity and sensitivity may vary in response to adaptation investments, future research should consider how these factors change over time and how they interact with allocation decisions.

Despite these limitations, this study offers valuable insights into the ultimate recipients of climate adaptation funding and highlights the need for more detailed geolocated funding data. To date, this study is the most comprehensive assessment of vulnerability-based targeting of international adaptation aid that simultaneously looks at multiple countries, multiple funds, and multiple years. A key recommendation emerging from this work is for climate financing organizations to enhance their transparency and data collection efforts regarding the subnational distribution of funds. None of the organizations included in the sample disclosed the subnational distribution of their funds in a consistent or easily accessible manner. To ensure that climate aid reaches the vulnerable communities that most require it, it is essential that we collectively advance towards more effective and transparent subnational tracing.

1.4 Methods

1.4.1 Summary of Variables

This study focuses on two main outcome variables at the municipal level: climate adaptation projects by total current USD, and climate adaptation projects by total project counts. The predictor variables explored are the three disaggregated components of climate change vulnerability: adaptive capacity, sensitivity, and exposure.

1.4.2 Selecting climate financing organizations and geocoding projects

I selected climate financing organizations from the Climate Fund Inventory (CFI) Database of the Organization for Economic Cooperation and Development (15) [4]. I restricted the search to organizations that operate in Latin America and the Caribbean (LAC) and provide funding for climate adaptation. I identified 35 climate financing funds that met these criteria, covering bilateral, multilateral, and private organizations.

For each fund, I downloaded the list of their projects explicitly labeled as adaptation-related from their websites. During this process, I discarded 23 funds: eight funds did not have any information online and did not reply to our emails, and twelve funds did not have any location-based adaptation projects in the countries in the sample (i.e., were based in other countries in LAC, only had mitigation projects in the sample countries, or their adaptation programs were not location-specific as is with the case of insurance programs), and three organizations had location-based projects in the sample countries, but no information at the level of municipality was found. Of the original list of 35, twelve funds remained. To find the sub-national location for projects funded by these twelve funds, coders (Research Assistants at the University of California at Santa Barbara and I) followed the 3-step methodology developed by the AidData

[4] This database is available at https://qdd.oecd.org/subject.aspx?subject=climatefundinventory.

Project (16) to geocode projects: 1) review project documents and associated information to identify subnational locations ("geoparsing"); 2) match the location information to the list of mapped administrative units for the country ("georeferencing"); and 3) assign specific latitude and longitude coordinates to each project ("geocoding").

Not all the projects could be tracked to the municipal level, as some of the organizations did not provide any sub-national location information. We collected location data for all administrative levels available and any additional location information available (e.g., nearby bodies of water, national parks, community names, etc.) along with a certainty level (assigned by the coder) for the assigned location. Projects for which only the national level was listed were coded as such, and no assumptions were made about the project benefiting all municipalities equally. The final dataset is described in Table 1.1 below.

For multi-municipality projects, I divided the total project investment equally among all municipalities. Because this is a strong assumption and one that affects the validity of the findings, I also aggregated the project data as project counts, which only indicates how many projects have impacted the municipality without assuming an equal distribution of funds. One of the outputs of this process was the creation of the first set of maps of hot and cold spots of climate adaptation funding for Central America and the Caribbean. I created these maps with administrative boundary data from the Food and Agriculture Organization (17).

1.4.3 Climate Change Vulnerability

I separated climate change vulnerability into its three core components: climate change exposure, adaptive capacity, and sensitivity. Data sources and indicators are listed below and summarized in Table 1.2 below.

Climate Change Exposure

In its 6th assessment report, the IPCC (18) developed five possible future narratives for

Table 1.1: Climate financing organizations, unique projects, and geocoded records

Climate financing organization	**Unique projects**	**Records with adm2 information**	**Total amount (USD)**
Adaptation Fund	10	120	81,571,846.71
ASAP	4	184	71,680,816.08
Climate and Dev. Knowledge Network	2	15	422,248.11
FONTAGRO	4	27	3,132,578.00
GCCA	1	2	5,642,500.00
GEF Small Grants Programme	38	32	963,443.27
GEF (all other programs)	6	60	32,787,004.00
Germany's Int. Climate Initiative	5	35	20,107,725.55
Green Climate Fund	4	225	270,145,114.33
KfW	4	27	38,718,666.67
MDG Spain	3	14	10,463,636.36
The World Bank	6	76	124,789,000.00
TOTAL	87	817	660,424,579.08

Component	**Concept**	**Indicator**	**Source**
Exposure	Projected changes in climate	Max Temp of Warmest Month: Baseline - Projected 2021-2040	WorldClim
	Projected changes in climate	Min Temp of Coldest Month: Baseline - Projected 2021-2040	WorldClim
	Projected changes in climate	Annual Precipitation: Baseline - Projected 2021-2040	WorldClim
Adaptive Capacity	Access to basic needs	Access to water	Census
	Access to basic needs	Access to electricity	Census
	Access to basic needs	Access to water	Census
	Education	Adults w/only primary education	Census
Sensitivity	Age	Dependency ratio (infants + elderly / working age pop)	Census
	Minority population	% Indigenous populations	Census
	Sensitivity to disasters	Past disasters 2000 -2020 in counts/10,000 people: Dead, injured, and missing Homes damaged and destroyed Direct and indirectly affected	DesInventar

Table 1.2: Data sources and indicators used to construct the climate change vulnerability indices

shared socioeconomic pathways ("SSP"). These future scenarios refer to different combinations of changes in emissions and actions to combat climate change. For this study, I chose climate projections for SSP5, an energy-intensive scenario with the highest overall emissions of any SSP.

I used climate projections and historical climate data from the WorldClim database. The climate projection data are for the period between 2021-2040, are provided at a 30 second resolution, and come from 23 different General Circulation Models (GCM). The historical climate data, also at a 30 second resolution, is for the period between 1970 and 2000 and was used as a baseline. I extracted average monthly values for all the municipalities in the sample for three indicators: maximum temperature of the warmest month (°C); minimum temperature of the coldest month(°C); and annual precipitation (mm). I subtracted the 2021-2040 projected values from the baseline values to create a measure of climate change exposure along the three indicators. I calculated z values for the three indicators and averaged to form the climate change exposure index. Higher numbers correspond to higher vulnerability.

Adaptive Capacity Vulnerability Index

I used four indicators for adaptive capacity, three related to access to basic needs and one related to education: percentage of the population with access to water, percentage of the population with access to electricity, percentage of the population with access to sanitary toilets, and percentage of adults with only primary education or less. All the indicators were built with data from each country's census between 2010 and 2018. I calculated z values for the four indicators and averaged them to form the adaptive capacity index. Higher numbers correspond to higher vulnerability.

Sensitivity Vulnerability Index

I used three indicators for sensitivity: dependency ratio, percentage of the population that belongs to minority populations, and sensitivity to disasters. The first two indicators were built with data from each country's census between 2010 and 2018. The sensitivity to disasters indicator was built with data from the DesInventar [5] database and was based on disaster counts along three separate disaster metrics normalized by every 10,000 people: 1) deaths, injured, and missing; 2) homes damages and destroyed; and 3) direct and indirectly affected. The disaster data corresponds to the years 2005 to 2020. I calculated z values for the three indicators and averaged them to form the sensitivity index. Higher numbers correspond to higher vulnerability.

1.4.4 Analysis

I used regression models with fixed effects to assess the relationship between climate change vulnerability and climate adaptation investments. Models 1 and 2 correspond to a cross-sectional analysis with fixed effects at the level of country where the variables that vary over time, adaptation investments and sensitivity, are aggregated so a single value of each represents each municipality. Models 3 and 4 are models based on a panel analysis with fixed effects at the level of country and year. The model specifications are as follows:

Main Models (Additive Models)

Cross-sectional analysis - Models 1 and 2

$$\text{Adapt}_i = \beta_0 + \beta_1 \text{Adap Cap}_i + \beta_2 \text{Sensit}_i + \beta_3 \text{CC Exposure}_i + \beta_4 \text{Country} + \varepsilon \tag{1.1}$$

Where:

[5] The DesInventar database was created by the United Nations Office for Disaster Risk Reduction (UNISDR) within the Sendai Framework for Disaster Risk Reduction. It is populated by individual countries and records disaster events, including, but not limited to climate-related events. Each event includes metrics of impact, such as human fatalities and number of homes affected. Each event is listed with location information, including the name of the municipality where the event occured.

- Adapt is the total adaptation investments for each municipality. In model 1 this is measured as total current USD and in model 2 this is measured in project counts.
- Adap Cap is the adaptive capacity vulnerability index.
- Sensit is the sensitivity vulnerability index.
- CC Exposure is the climate change exposure vulnerability index.
- Country is a factor of countries.

Both model 1 and 2 use country fixed effects and their standard errors are clustered at the country level.

Panel analysis - Models 3 and 4

$$\text{Adapt}_{it} = \beta_0 + \beta_1 \text{Adap Cap}_{it} + \beta_2 \text{Sensit}_{it} + \beta_3 \text{CC Exposure}_{it} + \beta_4 \text{Country} + \beta_5 \text{Year} + \varepsilon \quad (1.2)$$

Where:

- All the components are the same as in models 1 and 2, with the addition of:
- Year which is a factor of years.

Both model 3 and 4 use country and year fixed effects and their standard errors are clustered at the municipality level.

Interactive models 1 - 4 Interactive models 1 and 2 correspond to a cross-sectional analysis with fixed effects at the level of country, similar to the base models 1 and 2 described above. However the interactive models apply a multiplicative method, integrating the three independent variables—adaptive capacity, sensitivity, and exposure—to explore their combined impact on the dependent variable. The model specifications are as follows:

Interactive cross-sectional analysis - Interactive Models 1 and 2

$$\text{Adapt}_i = \beta_0 + \beta_1 \text{Adap Cap}_i * \beta_2 \text{Sensit}_i * \beta_3 \text{CC Exposure}_i + \beta_4 \text{Country} + \varepsilon \tag{1.3}$$

Where:

- Adapt is the total adaptation investments for each municipality. In interactive model 1, this is measured as total current USD and in model 2, it is measured in project counts.
- Adap Cap is the adaptive capacity vulnerability index.
- Sensit is the sensitivity vulnerability index.
- CC Exposure is the climate change exposure vulnerability index.
- Country is a factor of countries.

Both the interactive models 1 and 2 use country fixed effects, and their standard errors are clustered at the country level.

Interactive panel analysis - Interactive Models 3 and 4

$$\text{Adapt}_{it} = \beta_0 + \beta_1 \text{Adap Cap}_{it} * \beta_2 \text{Sensit}_{it} * \beta_3 \text{CC Exposure}_{it} + \beta_4 \text{Country} + \beta_5 \text{Year} + \varepsilon \tag{1.4}$$

Where:

- All the components are the same as in interactive models 1 and 2, with the addition of:
- Year which is a factor of years.

Both the interactive models 3 and 4 use country and year fixed effects, and their standard errors are clustered at the municipality level.

Chapter 2

Politics Biases the Allocation of International Funds for Climate Change Adaptation

Abstract: International donors are active in assisting low- and middle-income countries adapt to climate change. However, it can be challenging to ensure that aid reaches the locations that are most vulnerable to climate risks given the potential for national leaders to distort allocations to favored areas. We leverage an original dataset that tracks the sub-national targeting of international adaptation projects in six Central American and Caribbean countries to show that municipalities that are politically aligned with the national executive receive approximately 36.34% more international funding for climate adaptation than municipalities that are not aligned. We find evidence that this political bias diverts funds from areas of higher need to areas with lower need, with non-vulnerable aligned municipalities receiving on average between 41.2% and 62.4% more funds compared to non-vulnerable unaligned municipalities.

2.1 Introduction

The impacts of human-induced climate change are becoming increasingly evident, with the current global temperature already exceeding 1.09 °C above pre-industrial levels and projected to surpass the critical 1.5°C threshold in the near future (19). Consequently, the frequency and severity of extreme climate events are intensifying, disproportionately affecting vulnerable communities and people. Despite the growing recognition of the need for international financing to implement climate adaptation strategies in these vulnerable areas, there is ongoing debate regarding the effectiveness of climate finance in reaching the intended beneficiaries and addressing the specific challenges they face (20; 21; 22).

Partisan alignment is often a significant factor influencing the allocation of funds from central governments to smaller administrative units (23; 24). This pattern of clientelistic distribution has been extensively documented in a robust body of literature dating back to the mid-1980s (25; 26). The political logic behind this behavior is to maximize various forms of electoral returns (23; 27), such as securing re-election or strengthening political loyalty for the party (23; 28; 24). Notably, when mayors and presidents belong to the same political party or party coalition, a distinct form of partisan alignment emerges, which has been shown to bias the allocation of public goods and services in favor of aligned municipalities (27; 29; 30).

Recognizing the potential for climate adaptation efforts to be distributed according to political preferences, this study evaluates if partisan alignment drives the allocation of international financing for climate adaptation. It may be the case that international funds are able to leverage their oversight and planning capabilities to decrease distortions of funds at the sub-national level. However, if this is not the case, then the prevailing focus in international discourse about making sure the countries that are most vulnerable to climate change receive the bulk of funding may mask important sub-national distortions that prevent funding from getting to people most at need. We specifically evaluate whether Mayor-President political alignment results in more funding to aligned municipalities and estimate the total value of the distortion.

We use a novel dataset of geo-located climate adaptation projects at the level of municipalities, sourced from 12 climate financing organizations (Alberola 2024). The dataset documents climate adaptation projects funded between 2010 and 2020 across six countries: Panama, Costa Rica, El Salvador, Guatemala, Honduras, and the Dominican Republic. To assess the potential bias in the distribution of these funds resulting from partisan alignment, we combine municipal and general election data and use a close election discontinuity design to identify the causal impact of Mayor-President alignment on the allocation of international funding for climate adaptation at the municipal level. This approach follows a well-established methodology for studying intergovernmental transfers using close elections as a robust causal inference framework (29; 31; 32; 33; 28).

We find evidence that municipalities where the mayor and the president belong to the same political party receive a considerably higher number and value of climate adaptation projects. While the precise amount is sensitive to model specifications of the regression discontinuity design, at the cutoff, aligned municipalities receive a minimum of 36.34% (95% CI -0.80% - 87.20%) more funds compared to their unaligned counterparts. Our results show that this biased allocation diverts funds from municipalities with higher need to politically aligned municipalities with lower levels of vulnerability to climate change. We find that among the non-vulnerable municipalities, defined as those below the top 25th percentile in a composite vulnerability index, alignment with the central government was associated with receiving between 41.20% (95% CI 3.67% - 92.51%) and 62.42% (95% CI 11.07% - 137.5%) more funds in current USD and between 0.026 (95% CI 0.002 - 0.051) and 0.039 (95% CI 0.009 - 0.070) more projects in project counts compared to unaligned municipalities.

This study represents the first systematic investigation into the role of partisan alignment in biasing the distribution of adaptation funds in Central America and the Caribbean. Its findings highlight the need for improved tracking of subnational allocations and for more robust measures to counteract clientelism. The politically biased allocation of adaptation funds that this study uncovers threatens environmental equity and fair governance, thereby undermining global efforts to combat the impacts of climate change.

2.2 Theory and Motivation

International Finance for Climate Adaptation

Climate adaptation is inherently a multiscalar process, requiring collaboration across various levels of governance, from global to local scales (34), with municipalities, in particular, playing an essential role in adaptation planning (35). The importance of municipalities is largely due to the localized nature of climate change impacts and their role as fundamental institutional units (36). Despite their critical role, municipalities often face significant challenges in financing and executing projects, such as constrained political autonomy (35) and limited access to credit (37), which is particularly acute in developing countries (38).

Simultaneously, international funding for climate projects, whether from bilateral or multilateral sources, is a key source of financing for adaptation efforts. These funds operate under mandates set forth by key international agreements. The UN Framework Convention on Climate Change (UNFCCC) and the 2009 Copenhagen Accord underscore the need to prioritize adaptation strategies for “particularly vulnerable” developing countries, with a specific focus on the least developed countries and small island developing states (39; 2; 3). This prioritization, while consistently emphasized in international agreements, has mostly focused on the country level, with limited research on the sub-national distribution of funds in developing countries (9; 10; 11; 21).

Vulnerability to climate change is defined by a combination of adaptive capacity, sensitivity, and exposure, each contributing to the overall vulnerability of a community or social system (4; 6; 5). Despite progress in developing tools to assess vulnerability, their practical use in identifying vulnerable areas within countries is still limited (40; 8). The challenge of assessing the effectiveness of vulnerability-based targeting of adaptation aid is further complicated by the lack of both subnational vulnerability data and detailed allocation data for existing adaptation projects, as discussed in chapter 1. These gaps, particularly the vague directives for subnational allocation and the lack of transparency in fund distribution, create opportunities for the politically motivated misdirection of adaptation aid.

Central governments often serve as intermediaries between international funding sources and local governments, playing a significant role in influencing the subnational allocation of climate adaptation funds (11). While international organizations may have mandates to allocate funds based on vulnerability needs, this often conflicts with the realities of the political preferences of central governments that can influence the distribution process. Several aspects of the politics of climate adaptation have been examined in the literature, such as the tendency to prioritize visible but less effective actions for political gain (41), the risk of private capture of public assets (22), and the emergence of rent-seeking opportunities in adaptation investments, especially in large infrastructure projects (42). The role of partisan alignment bias, however, which is the topic of this investigation, has not been systematically studied.

Partisan alignment and the distribution of adaptation aid

Bias based on partisan alignment, a form of political favoritism, is a well-recognized issue in public spending that influences the distribution of funds from central governments to smaller administrative units within a country (23). This study focuses particularly on Mayor-President alignment. A growing body of research has consistently shown that central governments tend to favor politically aligned municipalities in the distribution of various public goods and services (27; 29; 30; 43). While the direct impact of partisan alignment on the distribution of adaptation finance is yet to be systematically explored, existing research in related areas such as foreign aid, environmental policies, and disaster relief provides valuable insights into potential patterns and expectations.

Although climate adaptation financing is distinct from other forms of foreign aid, insights from the foreign aid literature provide a theoretical framework for understanding the potential influence of political interests on subnational distribution. Foreign aid is generally seen as less susceptible to clientelism than domestic public funds due to donor-imposed conditions and external monitoring mechanisms aimed at enhancing transparency in development projects (44; 45). However, despite these safeguards, the possibility of politicians capturing foreign aid for clientelistic purposes remains a concern (46; 47). Politicians might also use foreign aid-funded projects to boost their electoral campaigns and claim credit for initiatives (48).

Additionally, if the allocation patterns of climate adaptation funds mirror those of other environmental and disaster relief policies, there could be a potential for bias along party lines. This concern is supported by recent studies in Brazil: one study found that the central government preferentially established protected areas in unaligned municipalities (30), while another noted that aligned municipalities received higher disaster declaration rates (49). These findings highlight the strategic motivations of political actors in using foreign aid, environmental policies, and disaster relief to secure electoral support, claim credit for projects, or reinforce political alliances.

Expectations based on actors, their preferences, and their constraints

The allocation of international environmental aid is influenced by the preferences and constraints of international donors and recipient countries (11). We can characterize this interaction using principal-agent theory, where international donors act as principals who partially delegate the task of subnational allocation of aid for adaptation to sovereign states, the agents. In this framework, the preference of international donors is to distribute funds based on objective criteria of need, while the preference of central governments is to distribute funds based on political strategy that maximizes electoral returns. Although international donors and national governments may have competing preferences, they also have to cooperate to bring projects to fruition, which precludes either party from consistently imposing their preferences unilaterally.

Given these dynamics, which distribution pattern should we expect to prevail in practice—the need-based distribution preferred by international donors or the political distribution favored by governments? Three factors suggest that international adaptation financing should theoretically be a "hard case" for clientelism to emerge. First, the allocation of climate adaptation aid is directed by measurable criteria—adaptive capacity, exposure, and sensitivity to climate change—supported by scientific data and metrics. International donors have clear mandates and the technical capacity to allocate aid based on these criteria. Second, the involvement of international donors in distributing climate adaptation aid brings with it expectations of transparency, accountability, and adherence to international standards. Furthermore, since many of these funds are distributed as loans, there is a heightened expectation for accountability and transparency, unlike domestic funds, which might be subject to less stringent auditing and public scrutiny. Finally, although adaptation aid is frequently likened to a type of disaster management aid, its long-term focus distinguishes it from emergency aid, which is usually distributed quickly to address immediate crises. Unlike disaster aid, which is known to be susceptible to political distortions, the long-term perspective of adaptation aid should facilitate more deliberate and rational distributions. These elements collectively suggest that climate adaptation financing should be largely immune to the influences of political patronage and clientelism. Nonetheless, empirical and anecdotal evidence from prior research described in chapter 1 suggests that adaptation funds may still be subject to political distribution.

In addition to considering whether political biases drive the distribution of funds, it is also important to consider what the implications of this type of distribution may be. A clientelistic distribution of adaptation funds may not necessarily lead to distortionary outcomes where funds are diverted from areas of high need to areas of lower needs. We can imagine a scenario where climate vulnerability needs are so high and funding scarcity is so extreme that, even with political bias, resources are still directed toward areas with high need. However, the more concerning scenario is that political bias leads to a disproportionate distribution of resources toward politically aligned areas with low vulnerability, thereby diverting essential funds from areas with higher need. In this distortionary scenario, political alignment bias would enhance an area's likelihood of receiving funds, even if there are other areas that are objectively more vulnerable to climate change.

To investigate the potential role of clientelism in the distribution of funds, we analyzed the distribution of adaptation funding from 12 climate financing organizations over the period 2010 to 2020 to 1,358 municipalities in six Central American and Caribbean countries. We compared funding allocations between municipalities that were politically aligned with the central government and those that were not. For our purposes, a municipality was considered politically aligned if its mayor was from the same political party as the president. We used a close election regression discontinuity design to analyze the differences in allocations between these two groups of municipalities. To evaluate whether the observed distribution of funds was distortionary, we compared the funds and the probability of receiving a project between vulnerable and non-vulnerable municipalities, both when they were aligned and when they were not.

2.3 Methods

2.3.1 Research questions and hypotheses

Our primary research question explores the impact of alignment between mayors and the president on the allocation of climate adaptation funding to politically aligned municipalities. Our null hypothesis (H_0) is defined as follows: Mayor-president alignment does not lead to an increase in climate adaptation funding for aligned municipalities. Additionally, we examine whether observed political bias in fund distribution results in a distortionary allocation, where areas of lower vulnerability but politically aligned receive more funds. The null hypothesis (H_0) for this question is formulated as: Mayor-president alignment does not result in a distortion of the distribution of climate adaptation funding away from areas in need towards areas with low need but that are politically aligned. The data sources and analytical methods used to investigate these questions are described below.

The outcome variable in this study is the international adaptation funding allocated to municipalities, measured in two ways: $Y1$ represents climate adaptation projects by total current USD at the municipal level, transformed as $\log(\text{total USD} + 1)$, and $Y2$ represents the total project counts of climate adaptation projects at the municipal level. The predictor variable is a binary indicator of party alignment between elected municipal mayors and the country's president's party. We use the win-loss margin in mayoral elections to determine treatment entry and set bounds to subset close elections in the regression discontinuity design. Additionally, we include three disaggregated components of vulnerability to climate change as covariates: adaptive capacity, sensitivity, and exposure to climate change.

2.3.2 Operationalization, measurement, and data sources

Climate financing organizations and geocoded projects

The outcome variables, international adaptation funding in total USD and in total project counts, are from the 2021 Adaptation Funding Database (Alberola 2024). This database covers 12 climate financing organizations and 87 distinct projects distributed to 817 municipalities as detailed in Table 1.1 Although the database covers projects between 2006 and 2020, only the data between 2010 and 2020 are used for this study.

Climate Change Vulnerability

Climate change vulnerability is conceptualized as 3 separate components –climate change exposure, adaptive capacity, and sensitivity– and we follow previous works in Central America and the Caribbean (40) to operationalize them in this context. Data sources and indicators are summarized in Table 1.2.

Partisan alignment

Partisan alignment data come from country-level electoral institutions. We used two metrics: alignment, which is a binary variable (aligned vs unaligned), and winning margin. Winning margin refers to the percentage of votes that the mayor aligned with the winning national party received as compared to the runner up (in cases where it won) or compared to the winner (in cases where it lost). Another way to understand this variable is that it represents the difference in votes received by the mayor that belongs to the presidential party and the votes received by its strongest competitor. In cases where the president's party won, the strongest competitor is the party with the second highest number of votes. In cases where the president's party lost, the strongest competitor is the party that won at the municipal level.

We collected alignment and winning margin data between 2010 and 2020 for the six countries in the study, Panama, Costa Rica, El Salvador, Guatemala, Honduras, and the Dominican Republic. In mixed years, the municipality is coded as aligned based on the duration of the alignment in months. Municipalities that were aligned for more than 6 months were coded as aligned for that year. This is a result of a feature of the fund database, which is coded at the level of year and not the month. Of the 13,038 records in the sample (all municipalities for 10 years) 8,090 are unaligned and 4,948 are aligned.

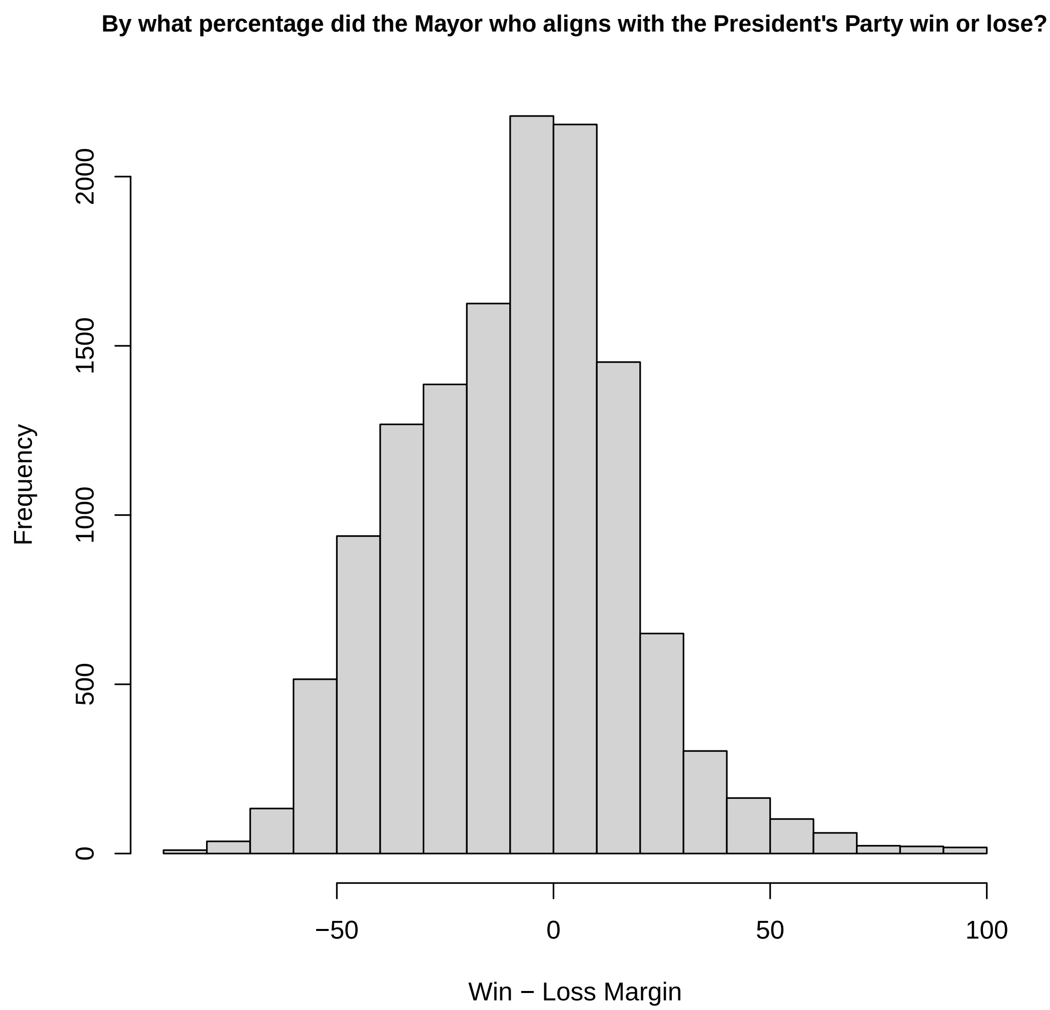

Figure 2.1: Distribution of the driving variable that determines entry into the alignment treatment. Values of 0 and higher represent the municipalities that are aligned. Those below 0 are not aligned. Proximity to 0 indicates a closer election.

Analysis

To determine whether aligned municipalities receive more funding, we use a sharp regression discontinuity design (RDD) (50; 51). Close election RDDs have been used to estimate the effect of party alignment on the distribution of resources to lower tiers of government (29; 31; 32; 33; 28). Regression discontinuity methods are well-suited for scenarios where inclusion in the treatment group—aligned municipalities in this case—sharply increases as a running variable, X, crosses a specified threshold (52). Our study used RDD to estimate the average treatment effect of political alignment on the allocation of adaptation funding, focusing on a close election discontinuity design. Essentially, we restrict the sample to municipality-years where the winning margin—which determines whether alignment occurred—was small.

The core principle of RDD lies in concentrating on observations near the cutoff point, with the assumption that treatment and control groups are similar in all aspects except for the treatment. In our context, this means that aligned and unaligned municipalities are comparable except for their political alignment. This proximity allows for the estimation of the local average treatment effect at the point of discontinuity. Formally, the average treatment effect at the cutoff x_0 is defined as:

$$\tau_{\text{RDD}} = \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x_0] \tag{2.1}$$

where $Y_i(1)$ and $Y_i(0)$ represent the potential outcomes under treatment and control, respectively, and X_i is the running variable. In our analysis, this effect is estimated by comparing the mean outcomes of the treated (aligned) units ($X_i \geq x_0$) and the control (unaligned) units ($X_i < x_0$) at the cutoff. The running variable is the win-loss margin, which represents the percentage of votes that the mayor aligned with the winning national party received as compared to the runner up (in cases where it won) or compared to the winner (in cases where it lost).

We estimate the following regression discontinuity design (RDD) model:

$$Y_i = \alpha + \tau D_i + \beta X_i + \gamma Z_i + \varepsilon_i \tag{2.2}$$

where Y_i represents adaptation investments measured in total current USD (in models 1 and 2) and in project counts (in models 3 and 4). D_i is an indicator variable that equals 1 if X_i is on the right side of the cutoff $c = 0$ and 0 otherwise. τ represents the discontinuity at the cutoff. X_i is the running variable (win-loss margin). β is the coefficient for the running variable. Z_i is a vector of control covariates: adaptive capacity, sensitivity, and climate change exposure, along with country-year fixed effects. γ is a vector of coefficients for the control covariates. ε_i denotes the error term. Standard errors are clustered by the electoral cycle. Finally, α is the intercept of the model.

We defined four models as follows: Models 1 and 2 focus on adaptation investments quantified in total USD, differing only in their polynomial order assumptions: Model 1 uses a first-order polynomial, while Model 2 uses a second-order polynomial. Similarly, Models 3 and 4 measure adaptation investments in terms of project counts, with Model 3 assuming a first-order polynomial and Model 4 a second-order polynomial. The choice of polynomial order is important as it can affect the accuracy and robustness of the estimated treatment effect. A first-order polynomial assumes a linear relationship between the driving variable and the outcome, whereas a second-order polynomial accounts for potential non-linearities. Using a higher-order polynomial typically enhances the accuracy of the approximation but also increases variability; therefore, the general recommendation is to keep the polynomial order low (53). We present results for both first-order and second-order polynomials to address potential concerns regarding model misspecification and the robustness of our findings. Primarily, we report the results from the first-order polynomial, adhering to the best practice of using the lowest odd order, which in our case also provides the most conservative estimate. All the models were analyzed using R statistical software (54) and the RdRobust package (55).

Assumptions for RDDs particularly for close-election RDDs, warrant a brief discussion before we proceed. We make four key assumptions in our models. The first two are the continuity of covariates and the continuity of the running variable around the zero cut point. We have verified that these assumptions are met, and the results of the covariate balance and the McCrary test for density in the running variable are presented in Figures B.9 to B.12 in Appendix B. The other two assumptions cannot be directly verified, but we believe they are reasonably satisfied. These assumptions are based on a recent critique by Marshall (56), which highlights two critical assumptions in close election RDDs at the discontinuity: (1) that the driving variable of interest (in our case, political alignment) does not influence the winning candidate's victory margin, and (2) no other variables affecting the closeness of the elections ("compensating differentials") also simultaneously impact the outcome of interest (in our case, the allocation of climate adaptation funds). When these assumptions are not met, the RD estimate will not effectively isolate the effect of the driving variable alone but will instead reflect the combined effects of the driving variable and these other factors.

Finally, to assess whether allocations are distortionary, we analyzed the distribution of funding in current USD across four distinct categories of municipalities, structured within a 2x2 matrix: Aligned Vulnerable, Aligned Not Vulnerable, Not Aligned Vulnerable, and Not Aligned Not Vulnerable. Additionally, we evaluated the likelihood of each group of municipalities receiving at least one project and the maximum number of projects in a given year (with four being the maximum number of projects received by any municipality-year). For this analysis, municipalities classified as vulnerable were those ranking in the top quartile of the climate vulnerability index previously mentioned, which takes into account adaptive capacity, sensitivity, and exposure.

2.4 Results

Results from models 1 and 2 (Table 2.1; Figures 2.2 and 2.3) suggest that aligned municipalities receive significantly more adaptation funds than unaligned municipalities. The results from model 1, which specifies a first order polynomial, suggest that at the cutoff, aligned municipalities receive on average 36.34% more climate adaptation funds than unaligned municipalities ($\alpha < 0.1$). The results from model 2, which specifies a second order polynomial, are considerably higher, suggesting that aligned municipalities receive on average 52.81% more climate adaptation funds than unaligned municipalities ($\alpha < 0.05$).

	(Model 1)		(Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Bias-Corrected RD Estimate	0.310		0.424	
Std. Err.	0.162		0.179	
z	1.909		2.372	
P>|z|	0.056		0.018	
95% C.I.	[-0.008 , 0.627]		[0.074 , 0.775]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Country, Year		by: Country, Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2389	2368	3044	2995
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.293	11.293	15.114	15.114
BW bias (b)	20.440	20.440	23.478	23.478
rho (h/b)	0.552	0.552	0.644	0.644
Unique Obs.	2929	1557	2929	1557

Table 2.1: Bias Corrected RD Estimate for models 1 and 2

Results from models 3 and 4 (Table 2.2; Figures 2.4 and 2.5) suggest that aligned municipalities receive more projects than unaligned municipalities. The main difference in the

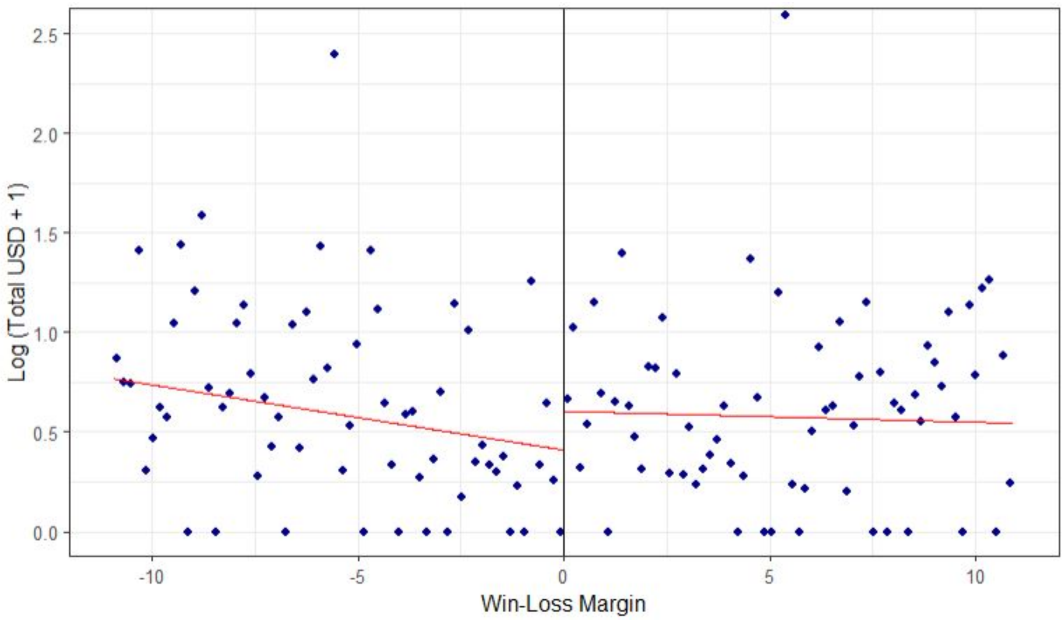

Figure 2.2: Model 1: RDD Estimate for Adaptation Investments measured as Log (Total USD +1) with country and year fixed effects, 1st order polynomial, and bandwidth around -11.293 and 11.293. The estimated effect of being aligned at the cut off is 0.310, which represents 36.34% more adaptation investments ($\alpha < 0.1$).

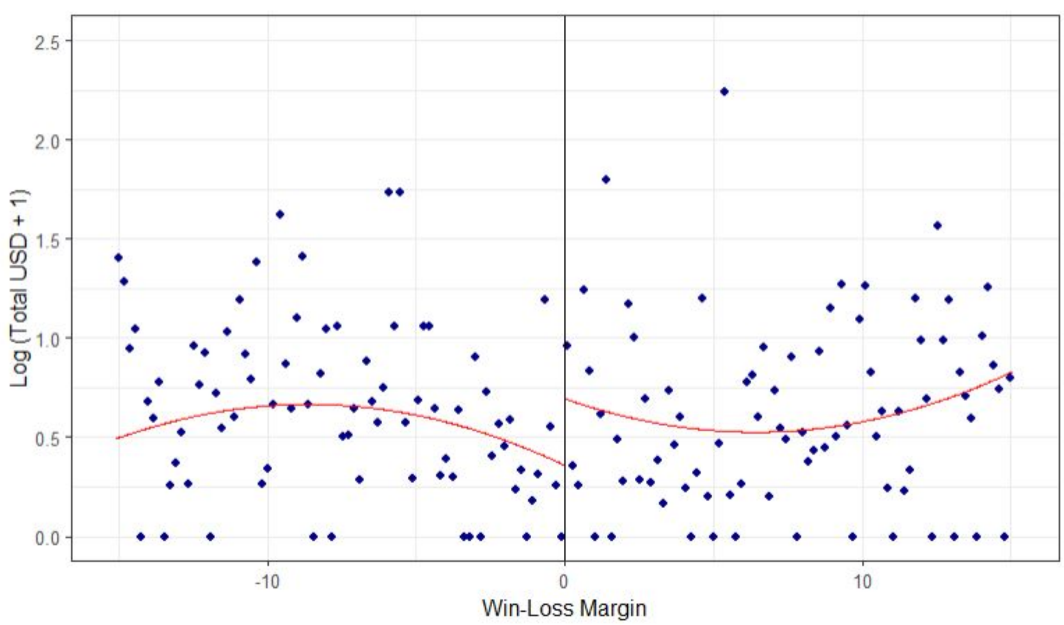

Figure 2.3: Model 2: RDD Estimate for Adaptation Investments measured as Log (Total USD +1) with country and year fixed effects, 2nd order polynomial, and bandwidth around -15.114 and 15.114. The estimated effect of being aligned at the cut off is 0.424, which represents 52.81% more adaptation investments ($\alpha < 0.05$).

specification of these two models is that model 3 assumes a first order polynomial and model 4 assumes a second order polynomial. The results from model 3 suggest that at the cutoff, aligned municipalities receive on average 0.022 more climate adaptation projects that unaligned municipalities ($\alpha < 0.1$) whereas the results from model 4 are slightly higher, suggesting that aligned municipalities receive on average 0.033 more climate adaptation projects than unaligned municipalities ($\alpha < 0.05$).

	(Model 3)		**(Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Bias-Corrected RD Estimate	0.022		0.033	
Std. Err.	0.013		0.014	
z	1.716		2.369	
P>|z|	0.086		0.018	
95% C.I.	[-0.003 , 0.047]		[0.006 , 0.061]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Country, Year		by: Country, Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2527	2503	3032	2947
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.991	11.991	14.907	14.907
BW bias (b)	21.811	21.811	24.091	24.091
rho (h/b)	0.550	0.550	0.619	0.619
Unique Obs.	2929	1557	2929	1557

Table 2.2: Bias Corrected RD Estimate for models 3 and 4

The analysis of the pooled data from the six countries yields consistent results, suggesting a strong and statistically significant effect of partisan alignment on the allocation of adaptation funds at the municipal level. To evaluate if different patterns emerged in different countries, we conducted a post-hoc analysis with disaggregated data for each individual country (for additional details, please see Tables B.3 to B.20 and accompanying discussion in Appendix

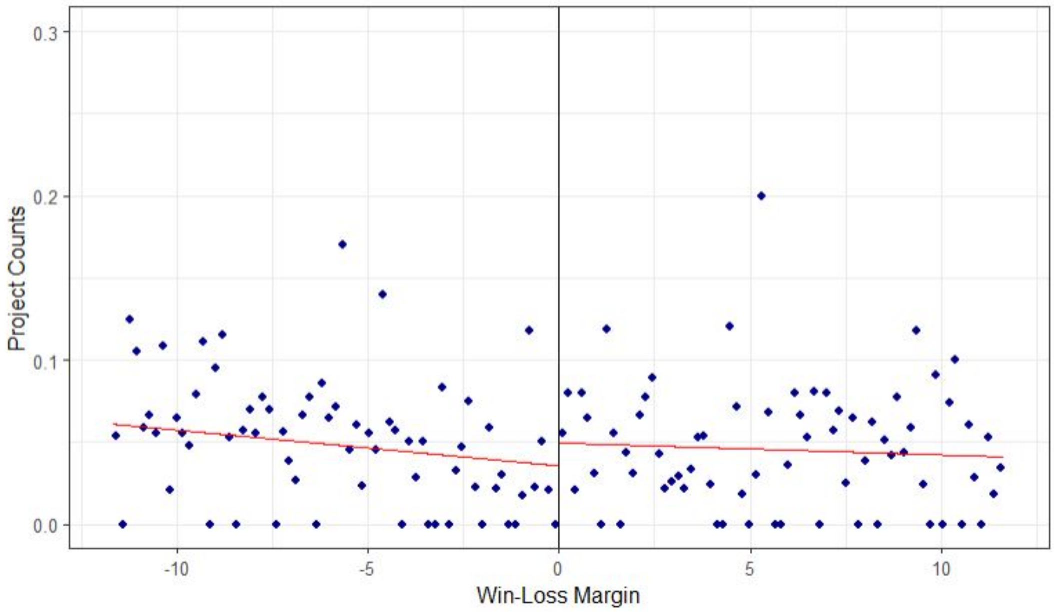

Figure 2.4: Model 3: RDD Estimate for Adaptation Investments measured in Project Counts with country and year fixed effects, 1st order polynomial, and bandwidth around -11.991 and 11.991. At the cutoff, aligned municipalities receive 0.022 more climate adaptation projects than unaligned municipalities ($\alpha < 0.1$).

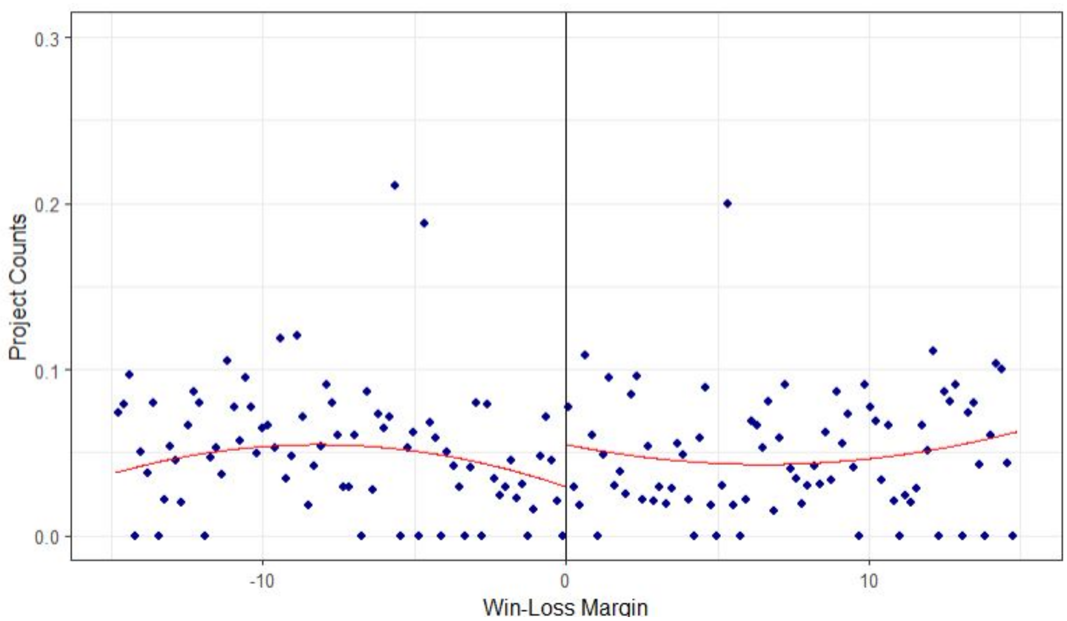

Figure 2.5: Model 4: RDD Estimate for Adaptation Investments measured as Log (Total USD +1) with country and year fixed effects, 2nd order polynomial, and bandwidth around -14.907 and 14.907. At the cutoff, aligned municipalities receive 0.033 more climate adaptation projects than unaligned municipalities ($\alpha < 0.05$).

B). This analysis yielded varied results: positive effects in some countries, negative effects in others, and no statistically significant effects in most of them. These inconsistent results are likely associated with the smaller sample sizes around the cutoff for the individual countries. In most of the countries, there was insufficient statistical power to detect an effect of the same size and significance as in the pooled data (please see Table B.21 in Appendix B). Despite these preliminary single-country results being inconclusive, they suggest an important area for further research into heterogeneous effects by country and potential correlations between country-specific factors and allocation outcomes.

Additionally, we conducted a post-hoc analysis to explore the relationship between funding mechanisms, local partnership types, and allocation outcomes. These preliminary analyses, detailed in Appendix B, suggest that grant-funded projects and those involving state actors as partners may be less susceptible to clientelism than projects with other funding mechanisms and those involving non-state actors. Normatively, we expected projects involving non-state actors, such as NGOs, to be less susceptible to clientelistic distribution due to their independence from governmental influence. However, these results suggest that the mechanisms designed by international donors to ensure more direct access to funding might not be sufficient to withstand clientelism and that non-state actors may still be influenced or co-opted by local political interests. Similarly to the potential heterogeneous effects by country, these results suggest important future avenues for research.

Finally, in our analysis of funding allocation distortions, we find that not vulnerable yet politically aligned municipalities received an average of $27,754.37 per year, in contrast to the $18,046.00 their unaligned counterparts receive (Table 2.3). This pattern extends to the likelihood of receiving both at least one project in any given year and the likelihood of receiving the maximum number of projects in any given year (Table 2.4). We find that not vulnerable yet politically aligned municipalities have a probability of 0.050 of being awarded at least one project in a given year compared to a probability of 0.042 for their unaligned counterparts, and a probability of 0.012 of receiving 4 projects in a given year compared to the probability of 0.011 of their unaligned counterparts.

	Aligned	**Not Aligned**
Vulnerable		
Total for group	37 524 645.00	58 885 829.00
Observations	1319	1928
Average per observation	28 449.31	30 542.44
Not Vulnerable		
Total for group	100 720 618.00	111 199 453.00
Observations	3629	6162
Average per observation	27 754.37	18 046.00

Table 2.3: Comparison of allocations in USD to municipalities grouped into four groups: Aligned Vulnerable, Aligned Not Vulnerable, Not Aligned Vulnerable, and Not Aligned Not Vulnerable

Group	Probability of at least one project/year	Probability of max projects/year
Aligned Not Vulnerable	0.050	0.012
Not Aligned Not Vulnerable	0.042	0.011
Aligned Vulnerable	0.049	0.013
Not Aligned Vulnerable	0.053	0.014

Table 2.4: Probabilities of project occurrences per year

We conducted pairwise t-tests to compare the means between the four groups. We find that, for results in current USD (Table 2.5), the means of the groups ”Aligned not-vulnerable” and ”Not aligned not-vulnerable” are statistically different at the conventional significance level of 0.1 (p-value = 0.095). This suggests a difference in the allocation pattern among non-vulnerable municipalities based on their alignment status. We do not observe the same pattern when comparing the means of the four groups in terms of project counts (Table 2.6).

Additionally, we find a statistically significant difference at the significance level of 0.1 (p-value = 0.095) between the means of the groups “Not aligned vulnerable” and “Not aligned not vulnerable” in current USD (Table 2.5). This suggests that among the unaligned municipalities, the level of vulnerability influences the allocation, which is normatively likely a positive outcome. However, it is concerning that among the non-vulnerable municipalities, the alignment status correlates with a difference in allocation. Taken together, these findings suggest a distortion in the allocation of funds where funds are diverted away from areas with higher need towards areas with lower need but that are aligned with the central government.

Group	Aligned Not-Vulnerable	Aligned Vulnerable	Not-Aligned Not-Vulnerable
Aligned Vulnerable	0.920	-	-
Not-Aligned Not-Vulnerable	0.095	0.225	-
Not-Aligned Vulnerable	0.920	0.920	0.095

Table 2.5: Pairwise comparisons among the four groups with means in current USD. We find statistically significant differences at the 0.1 significance level between the groups ”Aligned Not-Vulnerable” and ”Not-Aligned Not-Vulnerable” and between the groups “Not-Aligned vulnerable” and “Not-Aligned Not-Vulnerable”. We used t-tests with pooled standard deviation and p-value adjustment method BH.

Group	Aligned Not-Vulnerable	Aligned Vulnerable	Not-Aligned Not-Vulnerable
Aligned Vulnerable	0.90	-	-
Not-Aligned Not-Vulnerable	0.54	0.57	-
Not-Aligned Vulnerable	0.62	0.72	0.30

Table 2.6: Pairwise comparisons among the four groups with means in project counts. We do not find statistically significant differences among any of the groups. We used t-tests with pooled standard deviation and p-value adjustment method BH.

We estimate the magnitude of this distortion among municipalities considered not vulnerable using a regression discontinuity design. The specifications are similar to those used in the previous section, with the only difference being that the sample is restricted to municipalities below the top 25th percentile in the composite vulnerability index. We find that among the non-vulnerable, alignment is associated with receiving between 41.20% and 62.42% more funds in current USD (Table 2.7) and between 0.026 and 0.039 more projects in project counts (Table 2.8).

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Bias-Corrected RD Estimate	0.345		0.485	
Std. Err.	0.158		0.194	
z	2.186		2.503	
P>|z|	0.029		0.012	
95% C.I.	[0.036 , 0.655]		[0.105 , 0.865]	
Number of Total Obs.	9791		9791	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	6160	3631	6160	3631
Eff. Number of Obs.	1873	1753	2543	2317
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.470	11.470	16.422	16.422
BW bias (b)	23.155	23.155	28.375	28.375
rho (h/b)	0.495	0.495	0.579	00.579
Unique Obs.	2237	1165	2237	1165

Table 2.7: Bias-corrected RD estimate for Models 1 and 2 using a subset of municipalities considered not vulnerable under a 75% threshold, where those in the top 25th percentile are deemed vulnerable.

The 41.20% increase represents approximately \$26,992,321 in current USD in our sample of projects, which in turn represents 8.75% of the total amount of funding in our sample (\$308,330,546 in current USD). If a similar clientelistic pattern of at least this magnitude were present on a global scale, we could estimate that approximately \$3.66 billion annually of the average $41.75 billion (in 2021 USD) committed to climate adaptation efforts[1] could be misallocated each year to non-vulnerable places that are politically aligned, instead of going to vulnerable places. Certainly, much more additional research is necessary to determine if this pattern holds for other countries and regions, but these back-of-the-envelope calculations suggest a significant risk of clientelistic misallocation.

	(Model 3)		**(Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Bias-Corrected RD Estimate	0.026		0.039	
Std. Err.	0.012		0.016	
z	2.104		2.521	
P>|z|	0.035		0.012	
95% C.I.	[0.002 , 0.051]		[0.009 , 0.070]	
Number of Total Obs.	9791		9791	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	6160	3631	6160	3631
Eff. Number of Obs.	1904	1781	2458	2255
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.686	11.686	15.826	15.826
BW bias (b)	23.538	23.538	27.626	27.626
rho (h/b)	0.496	0.496	0.573	0.573
Unique Obs.	2237	1165	2237	1165

Table 2.8: Bias Corrected RD Estimate for models 3 and 4 using a subset of municipalities considered not vulnerable under a 75% threshold, where those in the top 25th percentile are deemed vulnerable.

[1] Five-year average based on adaptation commitments for 2017-2021 labeled as "adaptation-related development finance commitments" in the 2023 OECD's DAC External Development Finance Statistics database (57).

2.5 Discussion and Conclusion

Our findings suggest that partisan alignment between mayors and presidents significantly impacts the distribution of climate adaptation funds at the municipal level, leading to a diversion of funds from areas of higher need to areas with lower need. These findings are aligned with existing literature that has shown how clientelistic practices influence the allocation of public goods in favor of aligned municipalities. By extending this analysis to climate adaptation spending, this study not only contributes to the growing body of evidence that highlights the role of political alignment in shaping subnational resource allocation patterns, but also challenges the effectiveness of climate adaptation finance in reaching its intended targets.

Climate adaptation finance, as a newer type of funding distinct from other forms of development aid, has been expected to exhibit greater resistance to clientelism for several reasons. The global significance of addressing climate change, international commitments to equitable climate finance, reliance on scientific expertise in decision-making, and the humanitarian and environmental considerations involved all contribute to this expectation. However, the findings of this study strongly suggest that these expectations are not being met and that it is crucial to develop more robust measures to counteract clientelism.

A key question for future research pertains to why this political and distortionary distribution may fly under the radar of international donors. We hypothesize that within certain subnational regions, the allocation preferences of both key actors overlap and that this overlap tends to favor the preferences of clientelistic governments significantly. In this scenario two key constraints faced by international donors favor political distributions: the lack of standardized subnational climate vulnerability prioritization plans and the ambiguous, sometimes contradictory, definitions of adaptation and vulnerability. These constraints lead to a broad and flexible interpretation of 'need', where international donors focus on directing funds to poor areas, and as long as this criterion is met, clientelistic governments can distribute based on their preferences. In this way, international donors may consider their distribution preference met, overlooking that political considerations are significantly influencing the allocation of funds at the expense of the most climate-vulnerable areas.

Furthermore, while we could not determine with certainty if heterogeneous effects by country or by fund type exist, our preliminary analysis suggest potentially interesting avenues for future research. This could involve expanding the study to other regions, increasing the temporal scope, and conducting case studies to understand the factors that lead to adaptation funds being more or less susceptible to clientelism.

This study needs to be interpreted in light of two potential constraints. The first potential constraint is related to the comprehensiveness of the adaptation project dataset. Our analysis is limited to projects explicitly identified as adaptation efforts by donor organizations. Consequently, projects addressing adaptation needs through development, disaster, or other forms of aid not specifically tagged as adaptation initiatives are not considered. Additionally, our focus on location-specific projects means that non-location-specific adaptation initiatives, such as sector-specific projects that could benefit specific municipalities but are untraceable in our dataset, are also excluded.

Furthermore, because we could only include those projects that were traceable to the level of municipality, there is an inherent bias towards projects that are more transparently reported by donors. Nonetheless, this aspect of data incompleteness can be considered a beneficial feature for the reliability of our findings rather than a limitation. Given the premise that governments may allocate adaptation aid in a distortionary manner, the impacts of such distortions are likely to be minimized in the context of donors that are most transparent about their projects. Consequently, the incomplete dataset suggests that the estimated effects presented in this study represent a conservative estimate, offering a reliable lower bound of the actual impact of partisan alignment on adaptation financing. The second limitation of this research is the lack of time-varying data for some of the indicators that make up the climate vulnerability indices. Because adaptive capacity and sensitivity vary over time, and potentially in response to adaptation investments, future research should consider how these factors change over time and how they interact with allocation decisions.

Additional avenues for future research include exploring the underlying mechanisms through which partisan alignment influences the allocation of climate adaptation funds, investigating the long-term impacts of partisan bias on adaptation outcomes, and expanding the geographical scope beyond Latin America to gain a broader understanding of this phenomenon. In addition, considering how susceptible adaptation funds seem to be to political favoritism, it would be helpful to examine successful cases where political bias has been minimized and explore alternative strategies and institutional frameworks that promote more equitable outcomes.

Chapter 3

Empirical Insights into Hurricane Resilience Building: Testing Predictions and Evaluating Mitigation Strategies

Abstract: Building resilience to climate-related events like hurricanes is crucial for vulnerable areas worldwide. Yet, it can be very difficult to evaluate efforts to build resilience without observing the aftermath of some type of critical shock. We provide a framework for evaluating efforts to build resilience to disasters using nighttime illumination. In particular, we investigate the degree to which hurricane events cause immediate drops in nighttime illuminate in cities and towns following hurricanes and the length of time it take for these places to recover to pre-storm levels of illumination in the United States. Using this framework, we show that several commonly used measures of vulnerability to climate change, such as minority status and socioeconomic status, are predictive of a lack of resilience. We also find that, contrary to expectations, prior hurricane exposure is not associated with lessened impacts or shorter recovery times. Finally, we find that efforts to

create hazard mitigation plans to address climate-related risks do not seem to help local towns and cities increase their resilience in the face of hurricanes. Taken together, these results point to the needs to evaluate key interventions that aim to build resilience and to understand the productive conditions under which these interventions build resilience.

3.1 Introduction

Hurricanes and cyclones are becoming more frequent and severe due to climate change (58; 59; 60), heightening the urgency for better identification of vulnerable areas to prioritize and invest in resilience strategies and for evaluating the effectiveness of hazard mitigation interventions. To contribute to these areas, our study investigates which aspects of social vulnerability predict worse outcomes from hurricanes, whether prior experiences with hurricanes improve resilience in subsequent events, and the effect of adopting hazard mitigation planning (HMP) on hurricane impact and recovery. We find that all forms of social vulnerability worsen impact and slow recovery from hurricanes, and that neither the experience of a previous hurricane nor the adoption of an HMP is associated with better resilience outcomes.

Despite the growing urgency for better vulnerability targeting and for the evaluation of hazard mitigation strategies, these areas of research remain underexplored in systematic studies. Evaluating both the predictors of vulnerability and the effectiveness of interventions presents significant challenges, particularly in three areas: the lack of comparable metrics of resilience across different settings, the long-term nature of resilience-building which requires robust longitudinal studies to capture its true impact, and the difficulties in isolating the effect of specific interventions within the complex causal chain from planning to disaster outcomes.

To overcome the first challenge, we use nighttime illumination data, which measures not only direct access to electricity but, more generally, provides a validated measure of human activity and the status of infrastructure (61; 62; 63). After disasters, reductions in nighttime illumination can serve as an indicator of the extent of damage caused by the disaster (64; 65). We therefore use nighttime illumination data to create comparable trajectories or "resilience curves" of damage and recovery following hurricane landfalls. To address the two other empirical challenges, we employ an event study approach to assess the effects of vulnerability and mitigation planning on impact and recovery from hurricanes. We apply this approach to 17 hurricane events across ten states and U.S. territories between 2014 and 2023.

We began by examining the relationship between social vulnerability and hurricanes. Not only are hurricanes among the most devastating climate-related disasters, but they are also well known for disproportionately affecting communities with high levels of social vulnerability at all stages of the disaster. We use four measures of social vulnerability from the CDC/ATSDR Social Vulnerability Index (SVI)—Socioeconomic Status, Household Composition & Disability, Minority Status & Language, and Housing & Transportation—and examine how communities with above-median values in these categories fare. Overall, our findings suggest that all forms of social vulnerability worsen the impacts and recovery from hurricanes.

Next, we investigated whether places that experienced at least one prior hurricane between 2004 and the current hurricane strike experienced less damage and faster recovery as compared to places that did not experience hurricanes in that time window. We found that this prior experience of hurricanes did not predict reduced impact or recovery times, suggesting that these experiences either did not create a window of opportunity for resilience building or that this window was not sufficient to promote change.

Finally, we examined the role of a prominent hazard mitigation strategy in the US, local hazard mitigation plans. In the US, HMPs are a key component of disaster mitigation policy (66). Originally established under the Disaster Mitigation Act of 2000, these strategic documents are created at various levels of government to identify and reduce risks from natural hazards, including hurricanes (66; 67; 68). Despite their establishment as part of national emergency policy in 2000, the adoption of HMPs has not been uniform across the United States. This variation allows us to investigate whether the adoption of HMPs predicts improved responses during the initial impact and recovery after hurricanes. Contrary to expectations, however, our results suggest that adopting an HMP does not result in observable improvements in resilience.

Our study makes several contributions. First, we introduce a robust framework to examine vulnerability and resilience building. Previous research in these areas has been stymied by the lack of comparable metrics of resilience across diverse contexts. While much of the existing literature has focused on prospectively assessing vulnerability to hurricanes and typhoons (e.g., 69; 70), these metrics often lack validation against observed differences in storm impacts and recovery. We address this gap by demonstrating how resilience can be studied through a generalizable measure of economic activity and access to services– nighttime illumination – following critical events.

Second, we offer empirical validation for the use of the SVI thematic indices as predictors of impacts and recovery from hurricanes. We find that all vulnerability types encompassed by the SVI themes correlate with poorer outcomes, validating the SVI's effectiveness as a strategic tool for targeting resilience-building efforts in hurricane-prone areas.

Finally, we show that resilience building has generally been limited. Our findings suggest that even under conditions that could loosen structural constraints and facilitate change—such as experiencing a prior event or the implementation of an HMP—these factors alone are insufficient to overcome the significant challenges communities face in building resilience.

3.2 Background and theoretical expectations

Nighttime luminosity as a measure of resilience

Nighttime illumination provides a validated measure of human activity and the status of the built environment (61; 62; 63). After disasters, reductions in nighttime illumination reflect the availability of electricity, which serves as an indicator of the extent of disruption or damage caused by the disaster (64; 65). While nighttime illumination cannot capture the totality of well-being for people affected by disasters or resilience in the aftermath of critical events, it does capture several aspects of well-being that are relevant for resilience, including access to electricity, the status of infrastructure, the status of urban services, and ongoing economic activity. Such impacts of hurricanes are clearly visible in specific places affected by hurricanes, such as Puerto Rico in the aftermath of Hurricane Maria in 2017 (Figure 3.1). Using many such measurements over time allows us to examine differential impacts of hurricane exposure by jurisdiction at different times since a hurricane exposure.

We define resilience as the ability of human systems to absorb and recover quickly from perturbations like storms. Since nighttime illumination measures the totality of human activity and access to electricity, it enables us to see which areas are able to respond most effectively to storm exposures. It is possible that some recovery to baseline luminosity is not associated with long-term ability to withstand storm events, such as short-term patches and fixes like diesel generators. However, the totality of human activity being restored to pre-storm levels indicates that economic systems that support human well-being are resilient to the impacts of storms.

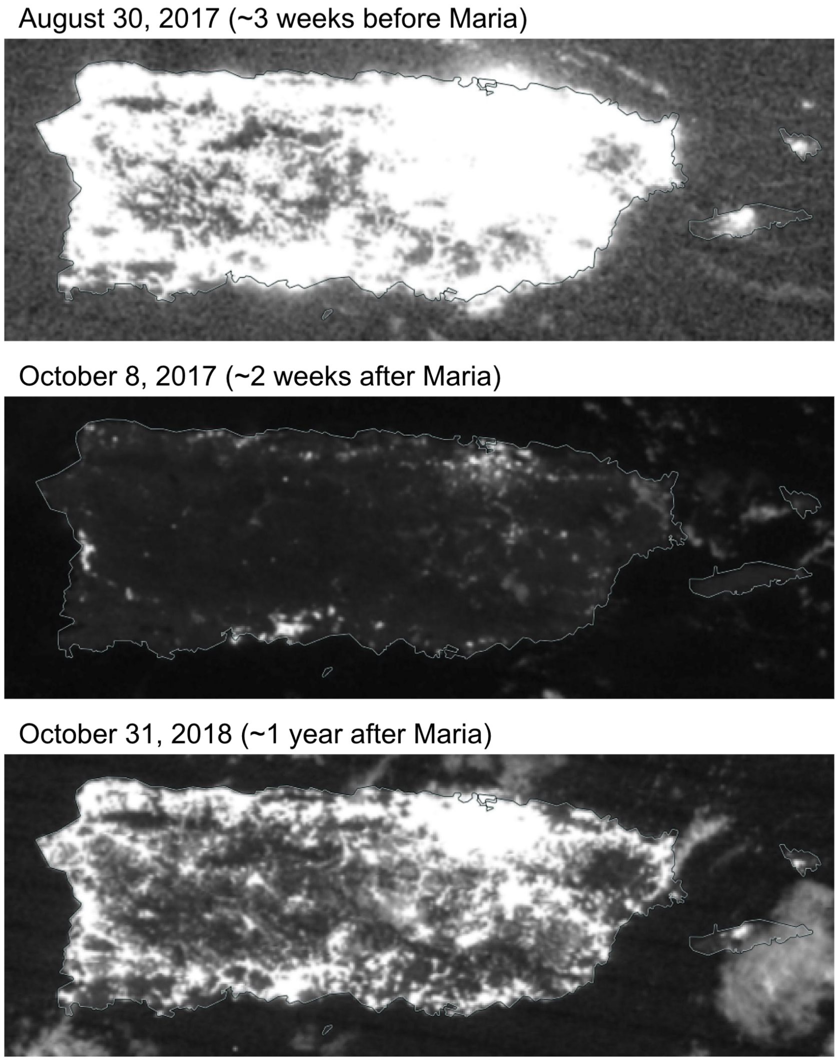

Figure 3.1: Visualization of VIIRS illumination data from before, immediately after, and one year after Hurricane Maria in Puerto Rico.

Social vulnerability as predictor of hurricane impacts and recovery

Socially vulnerable communities experience higher impacts from hurricanes along various metrics, including increased mortality rates (71), increased damage to residential structures (72), higher flood exposure (73), and higher population losses (74). During recovery, these communities also face delays in electricity reconnection (64; 75; 76), limited access to post-disaster assistance (77; 78), and greater socioeconomic, social, and health effects (79). Additionally, they often have lower access to preparedness and mitigation efforts (80; 81; 72).

While numerous studies have explored the relationship between social vulnerability and disaster experiences, they often focus on specific events or localized areas, providing valuable yet limited insight into broader trends and patterns. With the increased pressures of climate change and the predicted rise in the intensity and frequency of hurricanes, it is essential to determine if certain types of social vulnerability predict increased damages to aid in the allocation of resources towards resilience building.

To this end, we evaluate the relationship between hurricane impacts and four measures of vulnerability from the CDC/ATSDR Social Vulnerability Index (SVI): Socioeconomic Status, Household Composition & Disability, Minority Status & Language, and Housing & Transportation. These different composites of vulnerability likely influence hurricane impact and recovery in different yet interconnected ways. For example, socioeconomic status will likely affect the availability of financial resources to prepare for and recover from hurricanes. Households with a high proportion of elderly, disabled, or single-parent families may encounter greater physical and logistical challenges during evacuations and recovery efforts. Minority status and language may exacerbate vulnerability through reduced access to critical information and services. And, housing and transportation indicators may reflect both the structural quality of homes and the reliability of options for evacuation and recovery. Nonetheless, despite their interconnectedness, each measure of vulnerability may be associated with distinct challenges related to hurricane experiences, and therefore, some may have more predictive power of impacts than others. Our study aims to provide insights into this area by testing the predictive power of each vulnerability metric on hurricane impact and recovery outcomes. Our resilience curve approach, using nightlights, multiple events across multiple years, and spanning multiple jurisdictions, allows us to capture a comprehensive picture of the relationship between these metrics of vulnerability and hurricane outcomes in ways that have not been systematically studied yet.

Prior experiences with hurricanes

Prior experience with disasters has been found to increase resilience through both community and political processes. Experiencing disasters can influence social resilience in a community through several mechanisms, such as social learning, where effective actions become institutionalized for future use (82), by increasing social connectedness (83), and through the development of community-level adaptive and coping strategies (84). Disaster experiences can also heighten risk perception (85), raise awareness and knowledge, help individuals and communities predict consequences, and facilitate the development of preparedness strategies (86).

However, the experience of disasters does not always lead to resilience building. The link between disaster experience and the ability to take action is influenced by underlying institutional conditions, the magnitude of the disaster, and whether it is compounded by other adverse circumstances (87). Furthermore, community and individual access to resources play a critical role in whether they can implement mitigation behaviors (88). Finally, experiencing disasters can have the opposite effect and diminish resilience in many ways, such as by weakening adaptive capacity (87) and disrupting social networks through displacement (79).

In terms of political processes, disasters associated with natural hazards may provide a window of opportunity for resilience-building that helps local areas to reduce the risks of future exposures (89). Disasters can expand the options available to political leaders due to the increased salience of the hazard, widespread public demand for action, higher availability of central or international funds, and the opportunity to "build back better" after infrastructure failures (90; 91).

Local governments might use disasters to make long-lasting policy changes, reorganize their internal structures, and promote projects and programs to become more resilient. There is evidence to the contrary, however, showing the policy change in the areas of climate adaptation is not strongly associated with the experience of disasters (92).

Hazard Mitigation Plans and resilience building

The literature on disaster planning and resilience building spans multiple disciplines, including environmental science, urban planning, public policy, sociology, economics, engineering, and public health. Several mechanisms through which HMPs may build resilience can be identified from this diverse literature, particularly among studies that evaluate plan quality or assess outcomes and responses following disasters. Below, we group and briefly describe these mechanisms: institutional coordination, policy integration, risk identification, stakeholder participation, and fund and resource mobilization.

Institutional coordination among various levels of government and non-government actors, such as civil society, private companies, and local communities, is an essential component of disaster management (93; 94; 95; 96). Institutional coordination considerations are a key component in HMPs and are consistently included in quality assessments within the literature. Effective coordination can be affected by various factors, including the number and diversity of actors, competition for funding, the inherent unpredictability of disasters, resource scarcity or oversupply, and cost of coordination (97). During disaster response, the most frequently coordinated resource is information, followed by material, financial, and human resources (95). Despite its importance, failures in institutional coordination are prevalent during disasters and have often been identified as significant contributors to catastrophic outcomes (98; 99; 100). Furthermore, poor pre-disaster planning has been linked to these coordination failures (100).

Policy integration is a second area where HMPs can impact resilience building. They can influence future-oriented mitigation strategies and promote the integration of hazard mitigation into broader land use and development policies (94; 93). For instance, they may encourage the adoption of stricter building codes, zoning ordinances, and land-use planning that account for hazard risks. Additionally, they can promote the development of programs aimed at reducing risk (FEMA 2008), offering incentives or financial assistance (101) such as grants or tax incentives for property owners to undertake hazard reduction actions like retrofitting buildings. Finally, effective HMPs include mechanisms for carrying out policy-driven actions as well as for monitoring and updating plans, ensuring that local policies evolve with time and new information (102; 101).

Identifying risks is a core function of HMPs and is another mechanisms through which HMPs can build resilience. Risk is determined by the interplay between hazards, vulnerabilities, and available resources (71). Comprehensive risk and capability assessments are crucial to the success of HMPs, as they enable the development of practical and meaningful mitigation actions (94). HMPs include analyses of natural hazards such as hurricanes, tornadoes, and extreme temperatures (101), as well as social and administrative features, such as population distribution, existing land use, land supply, and future land demands (102). Poor understanding of and inattention to vulnerabilities before disasters has been linked to catastrophic consequences, particularly among socially vulnerable populations (71; 74; 73).

Stakeholder participation, and in particular, community-level participation, is another key mechanism through which HMPs can build resilience. Two important pathways emerge in the literature for this. The first involves the collection of local knowledge, which facilitates the assessment of risks and potential mitigation strategies that align with local needs and capabilities (102). Community involvement is a key parameter on which HMPs are evaluated, including the participation techniques implemented and the actors involved (101; 103; 68; 93). The second pathway focuses on community engagement and increasing awareness about ongoing mitigation efforts. Failures in community engagement have been linked to poor outcomes for minority and socially vulnerable communities. For example, in Puerto Rico with Hurricane

Maria, and in the US with Hurricane Katrina, post-hoc analyses found that communication and relief efforts were inadequate for different communities (79; 81).

Finally, HMPs can build resilience through fund and resource mobilization. HMPs help communities identify costs and sources of funding. They also allow jurisdictions to qualify for federal funding for mitigation activities after experiencing a disaster through the Hazard Mitigation Grant Program (HMGP)(104). If a presidential disaster declaration is issued, only jurisdictions with an approved HMP may qualify for HMGP funds, which support resilience-building efforts in the aftermath of a disaster (66).

In summary, HMPs enable states and local governments to identify and address risks before disasters occur and to create response and relief strategies for post-disaster scenarios (101; 67). The expectation is that planning can lessen the impact of natural hazards and reduce risks to populations and property (103). However, despite widespread endorsement of HMPs in the literature and practitioner spaces, there is a significant gap in empirical studies directly linking these plans and other mitigation policies to measurable improvements in disaster resilience and recovery efforts (104; 66).

Current HMP research primarily evaluates the quality of the plans and of the planning process, and they frequently reveal significant shortcomings in the overall quality of HMPs (101; 93; 103). Consequently, having an HMP does not necessarily ensure resilience building, as the plan itself may be inadequate. Additionally, there is a lack of clear empirical evidence linking specific practices or recommendations in HMPs to concrete disaster outcomes. Existing studies often focus on normative criteria based on established principles, frameworks, and FEMA requirements, but do not evaluate the effectiveness of those practices on measurable disaster outcomes. Our study aims to address this gap by providing clearer empirical insights into the effect of HMP adoption on resilience building.

3.3 Methods

Hurricane data

We obtained hurricane exposure data using NOAA's National Hurricane Center best track data. Our unit of analysis is the place, which is defined by the Census Bureau as a "concentration of population either legally bounded as an incorporated place, or identified as a census designated place (CDP)" and includes most cities, some towns, villages, and boroughs (105). We used the place boundaries from the Topologically Integrated Geographic Encoding and Referencing (TIGER) database from the U.S. Census Bureau. We extracted the date and time of exposure to hurricane wind speeds (64 knots and higher) for all the places in the sample between 2004 and 2023. The study sample covers 1,061 places across ten states and U.S. territories: Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, Puerto Rico, and the U.S. Virgin Islands. The final sample is restricted to the years 2014 to 2023 because those are the years for which we have illumination data. However, we still use hurricane hit data between 2004 and 2014 for analyses and covariates that reference prior hits.

To each place-year-month we assigned a binary variable for exposure to hurricane that is positive when a hurricane wind-speed radius of 64 knots intersects with the place boundaries. The map in Figure 3.2 illustrates the subset of places within the 10 states and territories included in our sample. These locations experienced at least one hurricane between 2014 and 2023. However, locations that experienced multiple hurricanes during this period are excluded if the intervals between these hurricanes were less than 23 months. This exclusion criterion is applied to minimize the potential confounding effects of rapid successive hurricane impacts on the same location.

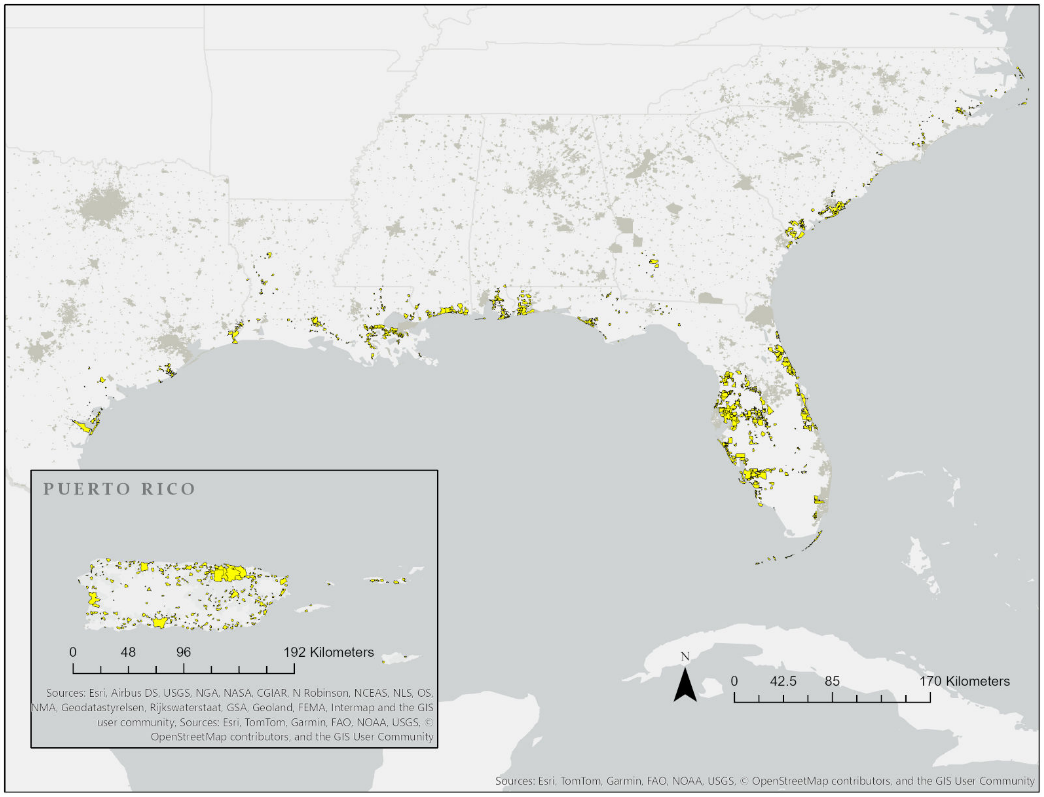

Figure 3.2: Subset of places (n = 1,061) within the 10 states and territories included in our sample that experienced at least one hurricane between 2014 and 2023

Nighttime luminosity data and resilience curves

Recent research has demonstrated that satellite nighttime illumination data from the Visible Infrared Imaging Radiometer Suite (VIIRS) is well-suited for measuring economic activity at smaller spatial scales compared to previous products (106). It is thus uniquely suited to measure resilience after hurricanes in comparable ways across many jurisdictions (64).

Our main outcome variable is luminosity before, during, and after a hurricane. We use composite images of monthly average radiance at night from the VIIRS Day/Night Band (DNB). These monthly composites are processed by the Earth Observation Group at the Colorado School of Mines, and are free and publicly accessible (107). We aggregated the average monthly radiance values (in Nano Watts / sq cm / steradian) for all the places in our sample between January 2014 and September 2023, totaling 117 images for each place. The monthly composites include lights from ephemeral sources, such as gas flares and fires, which requires some additional filtering. We filtered high luminosity values by identifying outliers using both global and local averages. Observations with luminosity values higher than both averages were flagged, and their luminosity values were replaced with the local average. For all other observations, the original value was kept, and any negative values were set to zero.

We investigate how different areas are impacted by hurricanes by examining how luminosity changes after exposure to a hurricane and the length of time it takes to return to pre-storm luminosity levels.

Using the VIIRS illumination data, we calculate the damage and recovery trajectories of every place in the sample that was exposed to a hurricane in event time, which sets the month of a hurricane strike as event month 0. The immediate drop in nighttime illumination can be interpreted as storm damage and the restoration of lights back to the baseline level can be interpreted as the time taken to recover the totality of electricity service and human activity to the hurricane. Since we are interested in responses to hurricanes, only places experiencing at least one direct hurricane strike from 2014-2023 when illumination data are available are part of the analysis.

For this model, we compare the level of illumination during each month before, during, and after a hurricane in the 12 months before and after a hurricane using the month prior and the twelfth month prior to the hurricane as the reference months. The data cover 17 different hurricanes that occurred between 2014 and 2023. In this model, we controlled for place, year, and month fixed effects.

Social vulnerability data

For the analysis of social vulnerability, we used four composite measures from the 2020 CDC/ATSDR's Social Vulnerability Index (SVI) (108) . We obtained these measures at the census tract level and later assigned them to the place level. To assign SVI values at the place level, we used the Geographic Correspondence Engine (Geocorr) tool from the Missouri Census Data Center (MCDC) (109). We used their place-to-tract allocation factor, with weights based on the percentage of the population within each census tract. The four composite indices are:

- Socioeconomic Status (Ranked Percentile or ”RPL” THEME 1)
- Household Characteristics (Ranked Percentile or ”RPL” THEME 2)
- Racial & Ethnic Minority Status (Ranked Percentile or ”RPL” THEME 3)
- Housing Type & Transportation (Ranked Percentile or ”RPL” THEME 4)

These composite indices are presented as percentile ranking values ranging from 0 to 1, with higher values indicating greater vulnerability. For our analysis, we create a binary indicator of high vulnerability, where places with values above the median are assigned a value of 1, and those at or below the median are assigned a value of 0.

Prior Exposure

We investigate whether places that experience prior hurricanes show less damage and faster recoveries during subsequent hurricanes as compared to areas that did not previously experience hurricanes. We define prior exposure as having experienced at least one prior hurricane between 2004 and the current hurricane strike. We interact a binary variable that assigns 0 to combinations of places and hurricane events where there are no prior hurricane strikes and a 1 where there are prior hurricane strikes.

We use a subsample of our universe of places where treated and control units are comparable. To create this sample, we used a matching algorithm with replacement, matching on the pre-trend values of luminosity for event months -12 to -1. We stratified the matching so that treated and control units were selected from within each hurricane month (hurricane cohort). This final subsample covers 364 treated units and 155 control units over seven different hurricane events.

We analyzed this sample using a fixed effects regression model where we interact the event month with the binary variable indicating prior hurricane experience. We include cohort by relative time fixed effects.

Hazard Mitigation Plans

We used data from the HMP dataset (Barnett et al., forthcoming), which details the dates of the adoption and expiration of local hazard mitigation plans for all the places in the sample. We conducted an event study analysis comparing the impact and recovery outcomes for places that had adopted HMPs prior to hurricane exposure to those that had not. We consider those with HMP adoption as treated units and those without as control units.

We define treated units as places that have had an HMP for five consecutive years prior to their hurricane exposure. Control units are defined as those that have not had any HMP coverage for the five years prior to the hurricane hit year. Under this definition, control units that have had HMPs during some of the five years prior to a hurricane hit have been excluded. We select the five-year time period as the main specification because HMPs last for five years before they expire. However, we test other specifications of treatment and control, for example, including as control units those with intermittent coverage, as well as other time periods and present those results in Appendix C.

We conducted a stratified matching process where we matched treated and control units within hurricane events (i.e., within cohorts) using a genetic matching algorithm. This approach ensured that treated units hit in a specific month were always matched to control units hit in the same month, preventing mismatches across different time frames. We used five covariates in the matching process: distance to the coast, population size, median income, percentage of the population deemed poor, presence of local government (as indicated in the Census of Governments dataset), and the total number of hurricanes before the first hit within the study period. This method allowed for a more accurate assessment of the predictive power of HMP adoption on hurricane impacts and recovery by accounting for potential factors that could influence both our outcome of interest (nighttime illumination) and our treatment (adoption of HMPs).

Our initial, full sample included 1,061 places, which, when combined with specific hurricane events, resulted in 1,212 place-hurricane observations from 2014 to 2023, covering 17 separate hurricane events. The resulting matched subsample for the HMP event study represents, as expected, a smaller number of observations and hurricane months compared to the full sample. The final sample of matched places for the five-year analysis using genetic matching covers 9 hurricane events, 353 treated units, and 104 control units.

Models

We estimate the difference in illumination of places relative to a baseline period of the month prior and twelve months prior to a hurricane striking the places. Since we are interested in responses to hurricanes, only places experiencing at least one direct hurricane strike from 2014-2023 when illumination data are available are part of the analysis. In particular, we estimate the following event study model to examine the baseline response to hurricanes:

$$Y_{ik} = \alpha + \sum_{k=T_0}^{k=-2} \beta_k I(k) + \sum_{k=0}^{k=T_1} \beta_k I(k) + \phi_i + \gamma_{\text{year}(k)} + \gamma_{\text{month}(k)} + \epsilon_{ik} \tag{3.1}$$

Where Y is the illumination level of places i in Nano Watts / sq cm / steradian at period k, defined as time before or after a hurricane strike for that jurisdiction. Period-wise estimates for each event time k before or after the hurricane strike are then obtained in comparison to the month prior and twelve months prior to the hurricane exposure, which are the omitted categories in the estimation. T_0 is the largest lag from the hurricane strike considered and T_1 is the largest lead from the hurricane strike considered. To account for time- and place-invariant factors, we include fixed effects at the level of the place ϕ_i, year $\gamma_{\text{year}(k)}$, and month $\gamma_{\text{month}(k)}$.

To estimate how the three different factors we investigate -social vulnerability, prior hits, and HMP adoption- impact the luminosity at different event times k across places, we use the same event study model but we interact the event time indicators k with a binary variable D_i that indicates the presence of the factor being tested. We therefore estimate the relative difference in "resilience curves" at each month between jurisdictions with and without the factor of interest.

For the interacted models, we use fixed effects that interact the hurricane month, which indicates the cohort (i.e., the unique hurricane event to which each observation corresponds) with the event month, which is a measure of time relative to the hurricane strike. In addition, for the HMP analysis, we cluster standard errors at the county level recognizing that much of the planning relevant to our study typically happens at this local level.

3.4 Results

We begin by describing the effect of hurricanes on night time illumination in the 1,061 places in the sample (Fig. 3.3). In the first month following a hurricane, we observe a large and statistically significant decline in the level of nighttime illumination. Because hurricanes occur at different times during the month, and illumination data are compiled by calendar months, it is expected that the illumination at month 0 is a combination of pre- and post- hurricane values and therefore the proportional decline in month 1 is greater than the apparent decline in month 0.

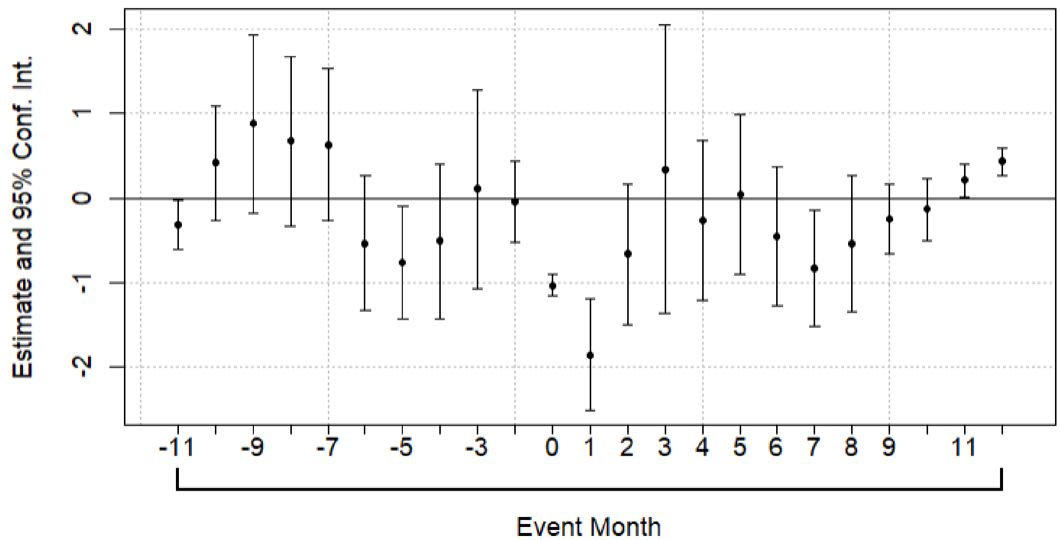

Figure 3.3: Proportional level of illumination during each month before, during, and after a hurricane using the month prior to the hurricane as the reference month for all places in the sample.

The baseline result indicates that it is possible to observe the impact of hurricanes in illumination, that these impacts persist for a number of months, and that recovery to baseline levels of illumination proceeds in an orderly fashion during a recovery period.

Next, we explore the effect of prior exposure. We find that places with prior exposure do not show differences in impact and recovery as compared to those not affected by prior exposures (Fig. 3.4). This finding suggests that experiencing a hurricane alone does not result in resilience building.

Next, we find that social vulnerability predicts heightened impact and slower recovery rates (Figures 3.5 - 3.8) and that this pattern holds for all four themes in the SVI: socioeconomic

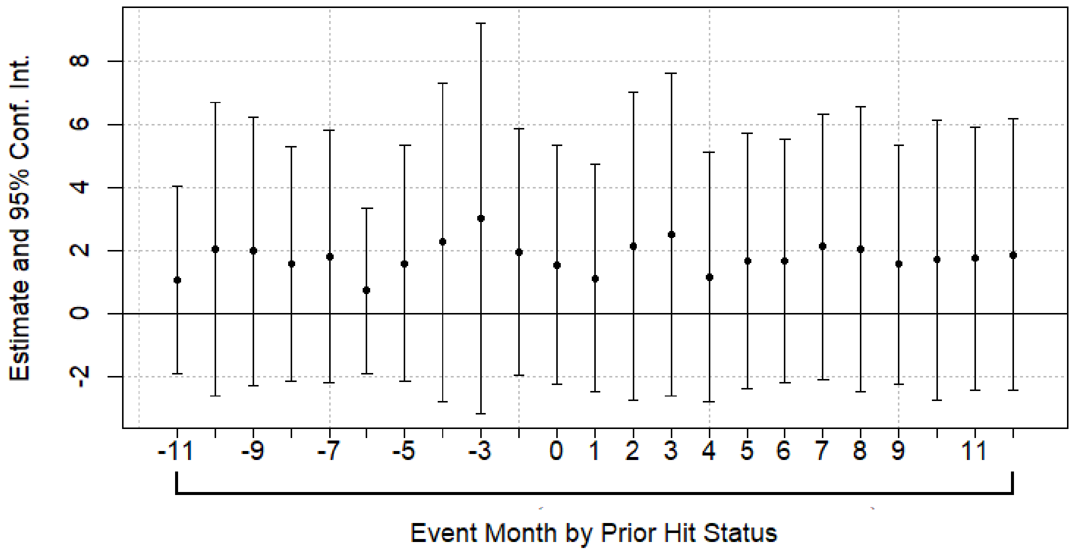

Figure 3.4: Relative proportional decline in illumination in places with prior exposure to hurricanes

status, household composition and disability, minority status and language, and housing type and transportation. We find that having high levels of vulnerability, defined as places with values above the median, in all of the themes is associated with worse impacts on impact month as well as on subsequent months.

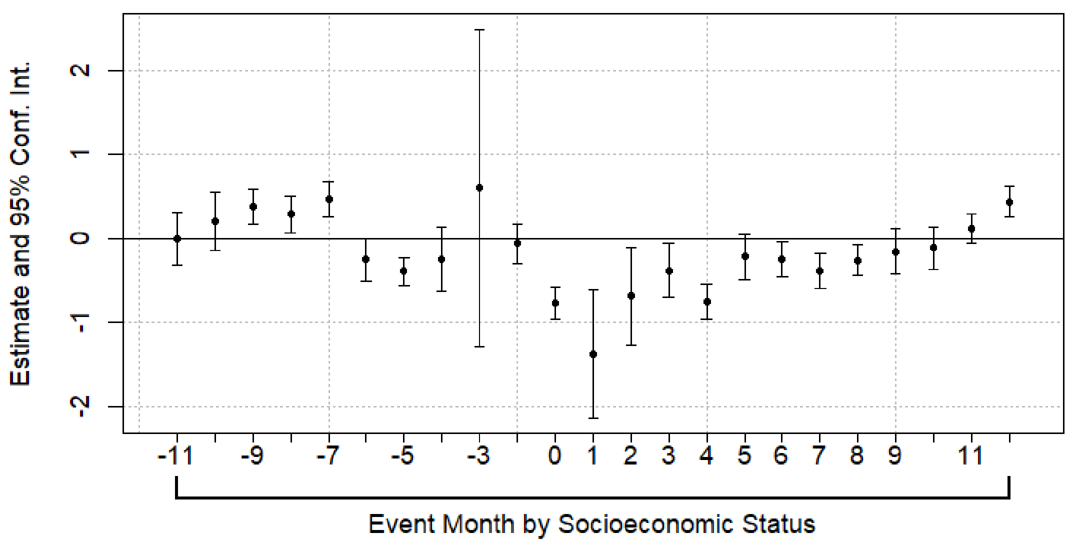

Figure 3.5: Relative proportional decline in illumination in places based on social vulnerability levels for Socioeconomic Status

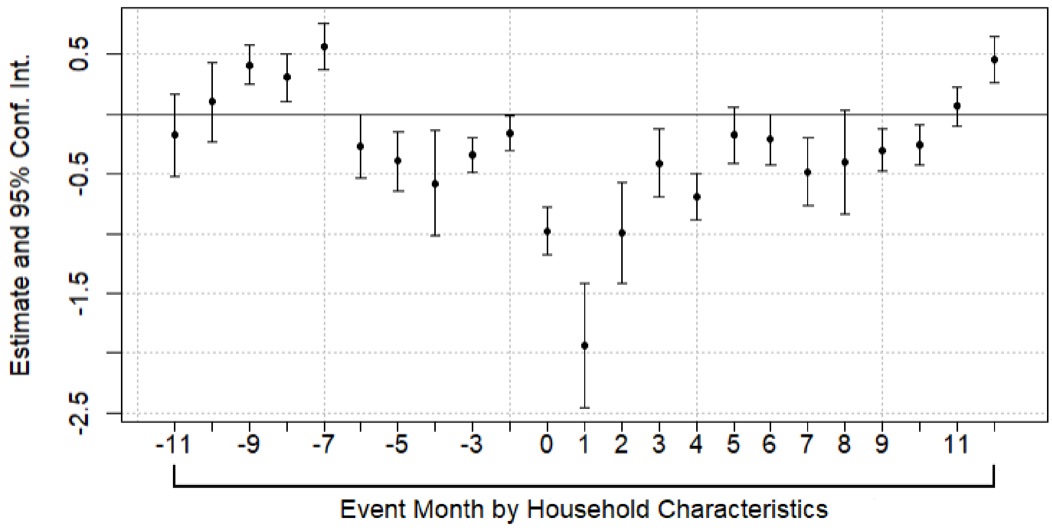

Figure 3.6: Relative proportional decline in illumination in places based on social vulnerability levels for Household Characteristics

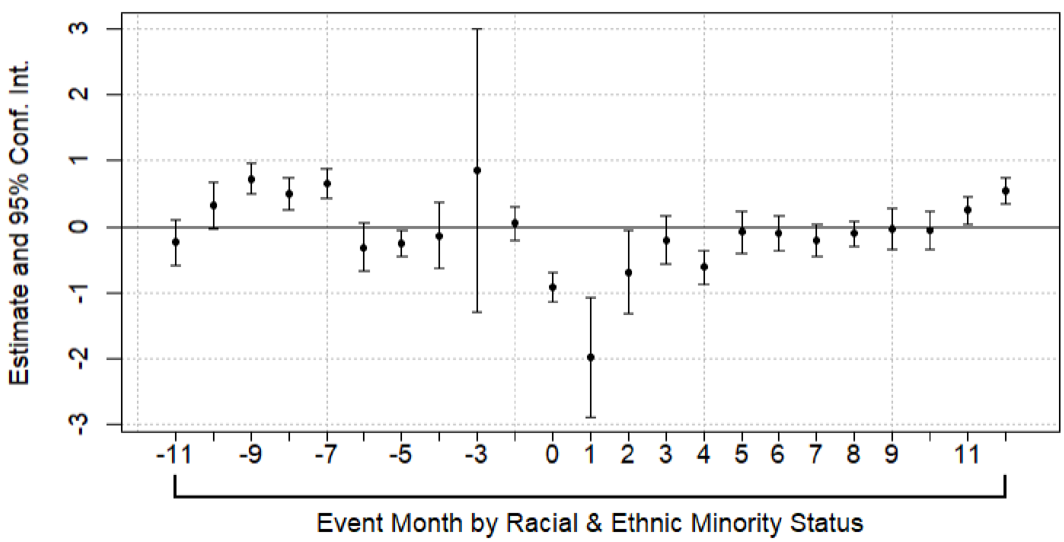

Figure 3.7: Relative proportional decline in illumination in places based on social vulnerability levels for Racial & Ethnic Minority Status

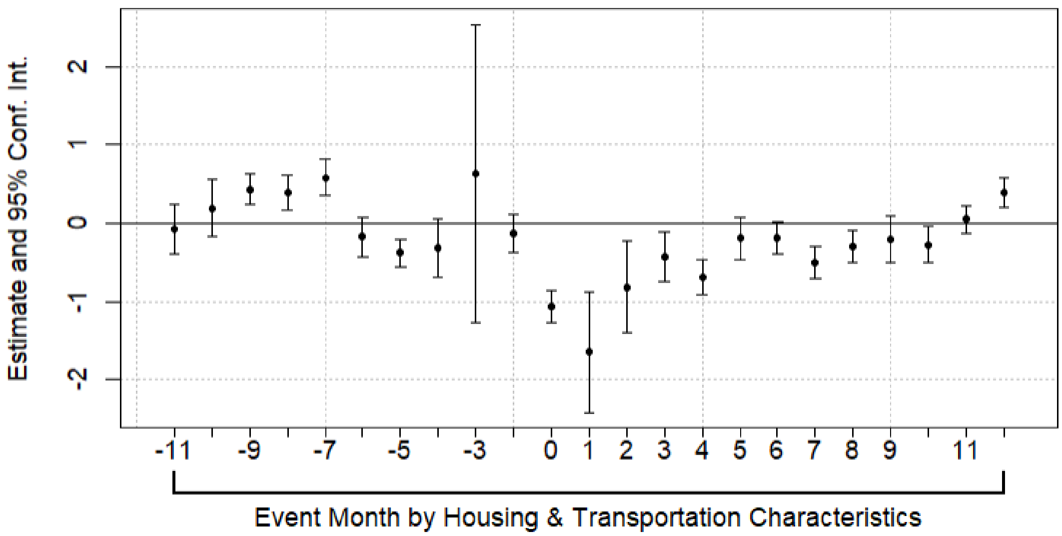

Figure 3.8: Relative proportional decline in illumination in places based on social vulnerability levels for Housing Type & Transportation

Finally, we found no statistically significant effect of HMP adoption on impact and recovery from hurricanes (Figure 3.9). In this model, we controlled for hurricane year (i.e., within-cohort) and relative time fixed effects. Standard errors were clustered at the county level. We matched the control and treated units using a genetic matching algorithm with replacement. In this specification, treated units are those with continuous HMP coverage in the five years prior to the hurricane impact, and control units are those without any HMP coverage in the five years prior to the hurricane impact.

We tested several additional specifications, including matching with different algorithms, lag years from one to six, and defining treatment and control differently, by excluding the restriction of consecutive coverage (please see Appendix C for additional results). Across all these specifications, we consistently found the same results of no effect of HMPs on outcomes, suggesting robustness of our findings.

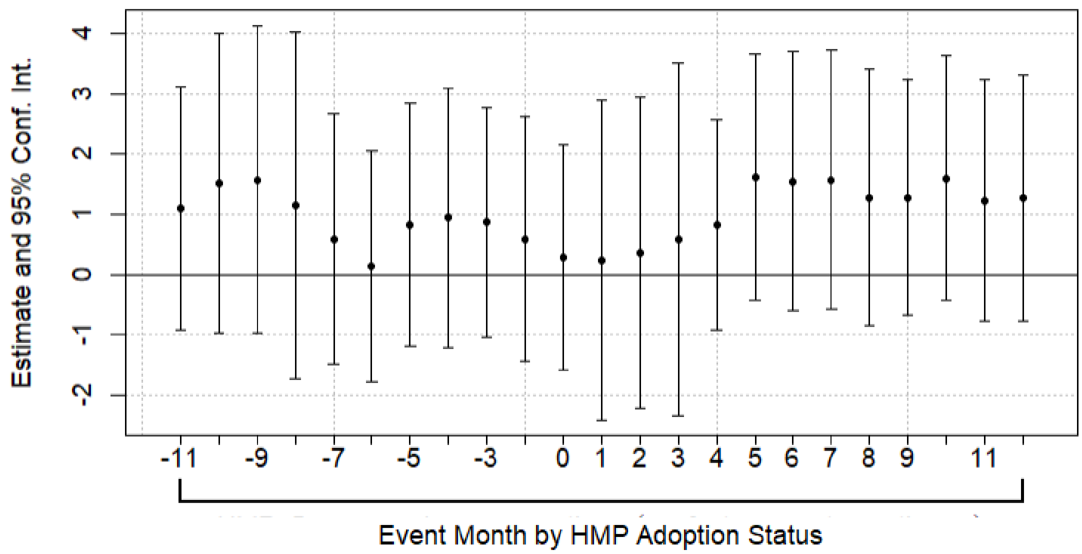

Figure 3.9: Comparison in decline of illumination in places with and without Hazard Mitigation Plans (HMP) implemented for at least five years prior to the time of hurricane

3.5 Conclusion

We have demonstrated several uses for satellite nighttime illumination data to study vulnerability and resilience. Starting with our evaluation of the predictive power of vulnerability on impact and recovery from hurricanes, we find that all types of vulnerability captured by the SVI themes are predictive of worse outcomes, suggesting that the SVI is a powerful tool for targeting resilience-building strategies.

Contrary to expectations, however, we also find that areas with prior exposure did not exhibit reduced impacts or shorter recovery times after a hurricane, as measured by nighttime luminosity. This underscores that the mere experience of a hurricane is insufficient for building resilience to future hurricanes, aligning with broader findings that without adequate resources and mitigation actions, experiencing any disaster does not necessarily lead to improved resilience (88; 110). In terms of political windows of opportunity, our findings align with recent evidence indicating that policy changes in disaster preparedness are not associated with storm exposures (92). We hypothesize that this may be due to the immediacy of disaster relief efforts, which often prioritize quick fixes over opportunities to build long-term resilience to future critical events.

We also find that, contrary to expectations, the adoption of HMPs was not associated with lessened impacts or shorter recovery times after hurricanes. A common finding in the HMP literature is the variation in the quality of these plans, with many only meeting the minimum criteria for adoption (101; 68; 93; 103), which could explain this outcome. In addition, the lack of systematic evidence linking best practices for HMP creation, such as increased community participation, as well as of the specific strategies proposed in them to quantifiable improvements in resilience adds complexity to the puzzle of why we don't see a clear resilience building signal with HMP adoption.

Borrowing from critical juncture theory (111; 112), we can view the experience of a hurricane and the adoption of HMPs as permissive conditions that loosen structural constraints and have the potential to promote change. However, without the right productive conditions, such as policy changes or an adequate influx of funding, the potential for substantial and lasting change remains limited. One recent study by Ji and Lee (104), citing a "dearth of evaluations" demonstrating the effectiveness of mitigation policy, explored the effect of a specific mitigation program, the Hazard Mitigation Grant Program (HMGP), and found that counties receiving HMGP funds showed significantly reduced property damage from future hazards. The HMGP is an example of a program that provides funding for long-term mitigation projects post-disaster. Their finding suggests that adequate funding is a key productive condition. Future research can therefore explore the causal and mechanistic chain from planning to resilience building and investigate under which productive conditions recipients of interventions seem to have better outcomes.

In addition to exploring the productive conditions that promote resilience building, our future work will investigate how political cycles and incentives affect the potential for building resilience to coastal hazards. A growing number of studies show that the maintenance of natural coastlines and mangrove forests is positively associated with reduced damages from storms (113). Other studies question the efficacy of traditional hardening interventions to build coastal resilience (114). We plan to investigate whether storms provide windows of opportunity, and under which conditions, to designate and effectively pursue certain types of responses, such as the preservation of wetland resources or the designation of coastal protected areas.

Appendix A

Supplemental Information for Chapter 1 - Uncovering the Exposure Gap: Rethinking Vulnerability Targeting in Climate Change Adaptation Funding

A.1 Table results for base and interactive models 1 - 4

In the main text, I presented the regression results of the main analysis graphically, using coefficient plots with 95% confidence intervals and the results of the interactive models using marginal effect plots. In this section, I present the same results in table format for a more detailed quantitative view.

Table results of base models 1 - 4

A one-unit increase in the adaptive capacity vulnerability index, moving from less vulnerable to more vulnerable, predicts, on average, a 212.68% [1]increase ($\alpha < 0.05$) in adaptation

[1]Because the scale is logarithmic, this values is calculated as $(1-e^{B})*100$, e.g., $(1-e^{1.140})*100 = 212.68\%$.

allocations and a 0.14 increase ($\alpha < 0.01$) in project counts over the entire time span of the study in the cross-sectional models 1 and 2. A one-unit increase in the adaptive capacity vulnerability index also predicts, on average, a 13.85% ($\alpha < 0.001$) increase in adaptation allocations in USD and a 0.01 increase ($\alpha < 0.001$) in project counts from one year to the next in the panel models 3 and 4.

Table A.1: Regression results for base models 1 - 4 where allocations are modeled as a function of Adaptive Capacity + Sensitivity + Exposure.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dep. Var.:	log(Total USD+1)	Project Counts	log(Total USD+1)	Project Counts
Adap. Capacity	1.140* (0.445)	0.139** (0.050)	0.130*** (0.027)	0.009*** (0.002)
Sensitivity	0.243 (0.499)	0.072 (0.057)	0.007 (0.036)	0.002 (0.003)
Exposure	0.260 (0.650)	-0.027 (0.078)	-0.011 (0.026)	-0.002 (0.002)
Fixed-Effects:				
Country	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes
S.E.: Clust. by:	Country	Country	Municipality	Municipality
Observations	1,358	1,358	19,012	19,012
R2	0.20307	0.19489	0.04297	0.03989
Within R2	0.02975	0.03453	0.00191	0.00169

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table results of interactive models 1 - 4

The results of the interactive models presented in the main text with marginal effects plots are here presented in table format for a more detailed quantitative analysis. In these models, allocations are modeled as a function of Adaptive Capacity x Sensitivity x Exposure. Exposure does not seem to have any predictive power in the cross-sectional models (interactive models 1 and 2) (Table A.2). In the interactive models 3 and 4, which use the panel version of the data, exposure on its own does appear to have some predictive power on allocations, but the direction indicates that with higher predicted exposure, allocations decrease by -6.89% ($\alpha < 0.05$) in USD and by -0.006 in project counts. Only adaptive capacity independently predicts higher allocations consistently in these models.

Table A.2: Regression results for interaction models 1 - 4 where allocations are modeled as a function of Adaptive Capacity x Sensitivity x Exposure.

	Interact Model 1	**Interact Model 2**	**Interact Model 3**	**Interact Model 4**
Dep. Var.:	log(Total USD+1)	Project Counts	log(Total USD+1)	Project Counts
Adap. Capacity	1.112* (0.408)	0.144* (0.042)	0.126*** (0.026)	0.010*** (0.002)
Sensitivity	0.076 (0.460)	0.034 (0.020)	-0.020 (0.037)	-0.001 (0.003)
Exposure	-0.238 (1.375)	-0.074 (0.174)	-0.071* (0.028)	-0.006* (0.002)
Adap. Capacity x Sensitivity	0.348 (0.463)	0.066 (0.055)	0.058* (0.026)	0.006* (0.002)
Adap. Capacity x Exposure	0.961 (0.922)	0.105 (0.090)	0.047 (0.036)	0.003 (0.003)
Sensitivity x Exposure	0.012 (1.204)	-0.016 (0.145)	0.077 (0.069)	0.005 (0.005)
Adap. Capacity x Sensitivity x Exposure	0.725 (1.035)	0.064 (0.126)	0.110** (0.041)	0.007. (0.004)
Fixed-Effects:				
Country	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes
S.E.: Clust. by:	Country	Country	Municipality	Municipality
Observations	1,358	1,358	19,012	19,012
R2	0.21801	0.2061	0.04445	0.04102
Within R2	0.04794	0.04798	0.00345	0.00287

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

A.2 Leave-one-out analyses

Both adaptive capacity and sensitivity are predictive of adaptation funding when examined in leave-one-out analyses (Tables A.3, A.4, A.5, and A.6). While the original models (Table A.1) suggest that sensitivity to climate change does not predict outcomes when all variables are combined additively, this analysis suggests that when adaptive capacity is excluded from the model, sensitivity emerges as a significant predictor of adaptation allocations. This is related to the overlapping nature of adaptive capacity and sensitivity, both rooted in closely related socioeconomic vulnerability metrics. Therefore, when included together in a model, adaptive capacity takes precedence as the primary predictor. Nonetheless, sensitivity still shows predictive importance when considered on its own. Notably, exposure does not predict allocations in any of the original models or in the leave-one-out models.

Table A.3: Leave-one-out robustness analysis for cross-sectional model 1, where allocations in current USD are modeled as a function of Adaptive Capacity + Sensitivity (leaving out Exposure), Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity).

	Model 1 without Exposure	**Model 1 without Adapt. Capacity**	**Model 1 without Sensitivity**
Dependent Var.:	log(Total USD+1)	log(Total USD+1)	log(Total USD+1)
Adaptive Capacity	1.174 (0.6162)		1.254** (0.2943)
Sensitivity	0.2519 (0.4535)	1.227*** (0.1261)	
Exposure		0.3897 (1.348)	0.2640 (1.234)
Fixed-Effects:			
Country	Yes	Yes	Yes
S.E.: Clustered by:	Country	Country	Country
Observations	1,358	1,358	1,358
R2	0.20245	0.19255	0.20281
Within R2	0.02899	0.01694	0.02944

Table A.4: Leave-one-out robustness analysis for cross-sectional model 2, where allocations in project counts are modeled as a function of Adaptive Capacity + Sensitivity (leaving out Exposure), Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity).

	Model 2 without Exposure	**Model 2 without Adapt. Capacity**	**Model 2 without Sensitivity**
Dependent Var.:	Project Counts	Project Counts	Project Counts
Adaptive Capacity	0.1359* (0.0490)		0.1734** (0.0436)
Sensitivity	0.0713* (0.0241)	0.1927** (0.0451)	
Exposure		-0.0116 (0.1568)	-0.0262 (0.1466)
Fixed-Effects:			
Country	Yes	Yes	Yes
S.E.: Clustered by:	Country	Country	Country
Observations	1,358	1,358	1,358
R2	0.19443	0.18445	0.19336
Within R2	0.03398	0.02201	0.0327

Table A.5: Leave-one-out robustness analysis for panel model 3, where allocations in current USD are modeled as a function of Adaptive Capacity + Sensitivity (leaving out Exposure), Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity).

	Model 3 without Exposure	**Model 3 without Adapt. Capacity**	**Model 3 without Sensitivity**
Dependent Var.:	log(Total USD+1)	log(Total USD+1)	log(Total USD+1)
Adaptive Capacity	0.1285*** (0.0263)		0.1331*** (0.0204)
Sensitivity	0.0067 (0.0361)	0.1189*** (0.0259)	
Exposure		0.0024 (0.0259)	-0.0109 (0.0256)
Fixed-Effects:			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by:	Municipality	Municipality	Municipality
Observations	19,012	19,012	19,012
R2	0.04297	0.04192	0.04297
Within R2	0.0019	0.00082	0.00191

Table A.6: Leave-one-out robustness analysis for panel model 4, where allocations in project counts are modeled as a function of Adaptive Capacity + Sensitivity (leaving out Exposure), Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity).

	Model 4 without Exposure	**Model 4 without Adapt. Capacity**	**Model 4 without Sensitivity**
Dependent Var.:	Project Counts	Project Counts	Project Counts
Adaptive Capacity	0.0091*** (0.0021)		0.0103*** (0.0017)
Sensitivity	0.0021 (0.0029)	0.0102*** (0.0022)	
Exposure		-0.0009 (0.0022)	-0.0018 (0.0022)
Fixed-Effects:			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by:	Municipality	Municipality	Municipality
Observations	19,012	19,012	19,012
R2	0.03986	0.03909	0.03987
Within R2	0.00166	0.00086	0.00167

A.3 Correlation of variables

The vulnerability indices for Adaptive Capacity, Sensitivity, and Exposure used in this analysis are constructed using a set of socioeconomic indicators and measures of anticipated exposure. This section explores the relationships among the ten indicators constituting these indices, the two outcome variables (total funding in current USD and the total number of projects), and three supplementary indicators employed elsewhere in this study. The objective is to asses the extent of correlation among these variables and to evaluate the potential for multicollinearity in the regression analyses. Correlation heat maps are provided to visualize the correlation coefficients among the variables under consideration. These maps are organized by country, with the cross-sectional dataset depicted in Figures A.1 through A.7, and the panel dataset illustrated in Figures A.8 through A.14. Adopting a threshold of 0.55 for significant correlation, I find that:

- The outcome variables, Project Counts and Projects in total USD are correlated in most countries (as expected)
- Adaptive capacity and sensitivity are also correlated in most countries (as expected). The Dominican Republic stands as the sole exception, which aligns with expectations given that its sensitivity index is constructed using just one indicator, the dependency ratio. This is because the other two indicators used in the other countries —percentage of indigenous population and past disaster losses— could not be included because the Dominican Republic does not have a measurable indigenous population, and their disaster data is not reliably recorded in the disaster database.
- Exposure index is not correlated with the other indices in any of the countries (as expected), but it is correlated with the outcome variable in USD in Costa Rica.

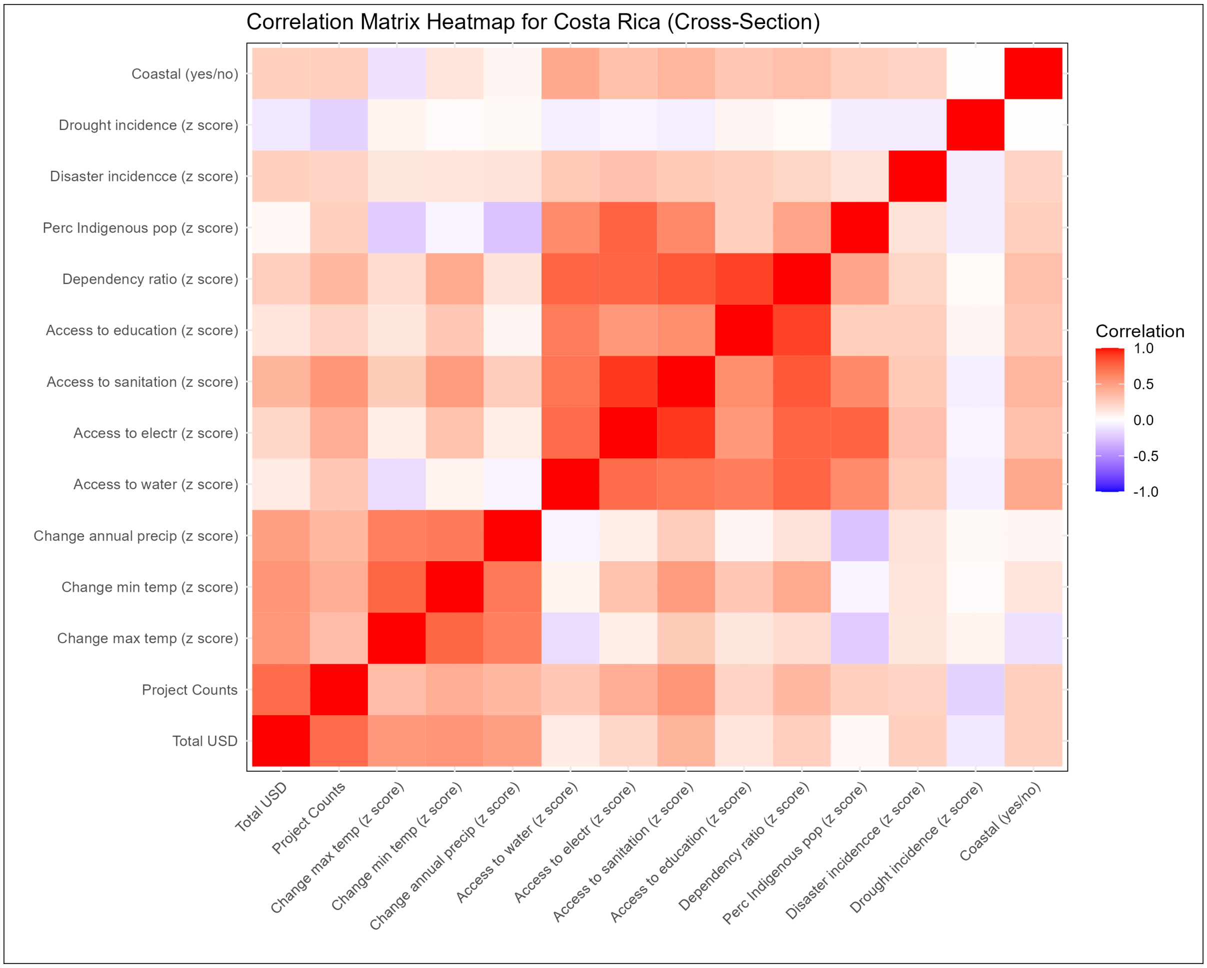

Figure A.1: Country-level correlation heat map of variables, cross-section data set, for Costa Rica

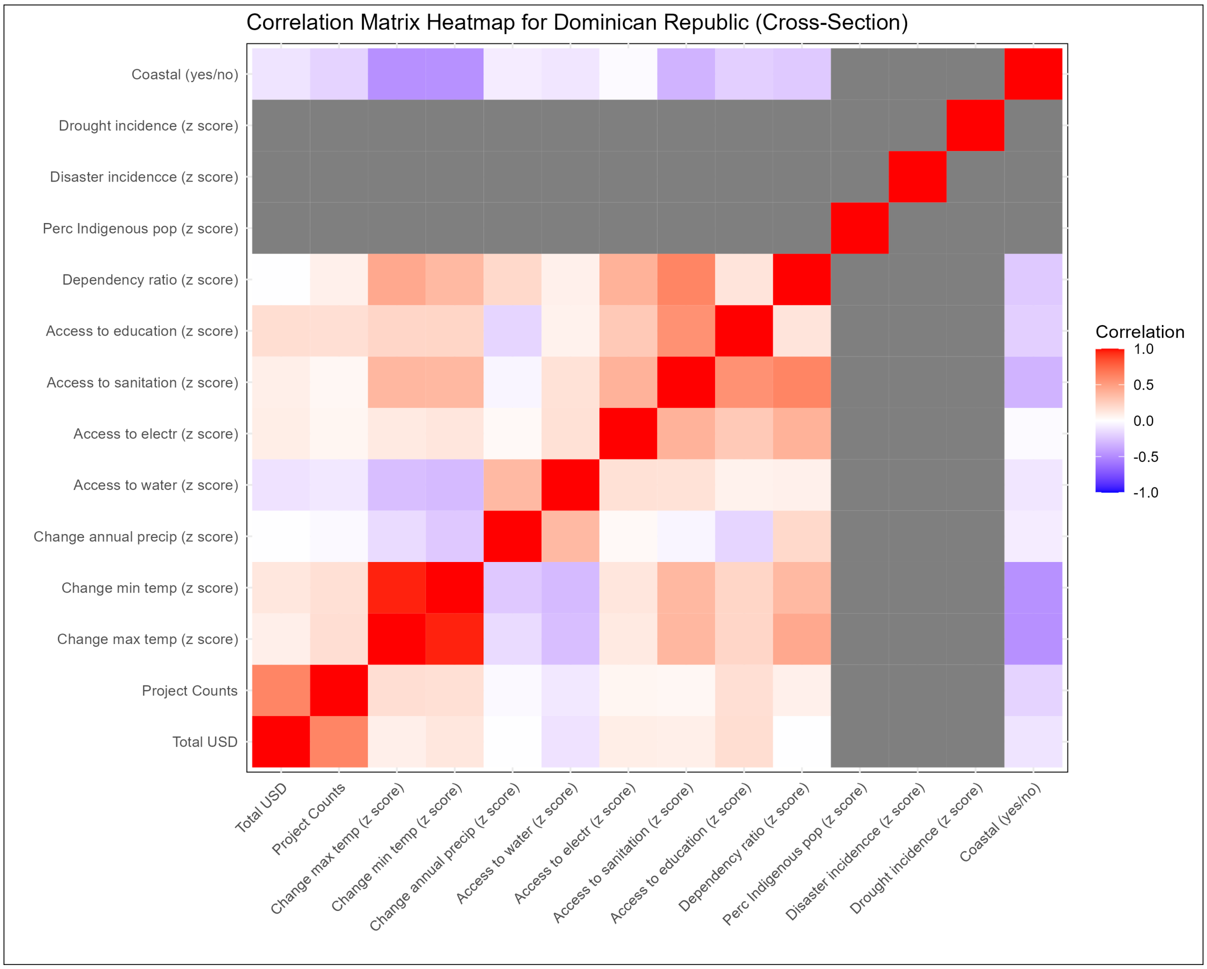

Figure A.2: Country-level correlation heat map of variables, cross-section data set, for the Dominican Republic

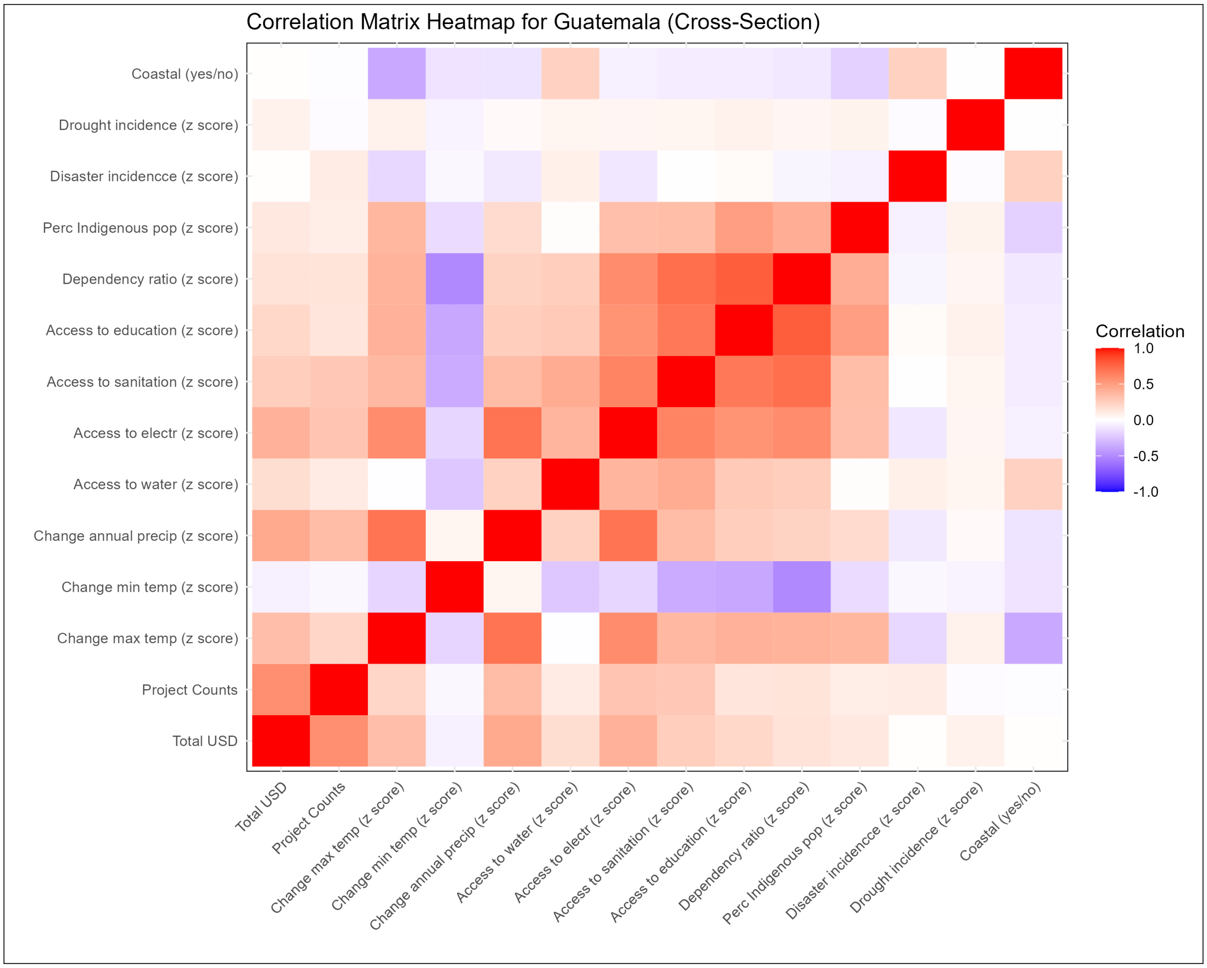

Figure A.3: Country-level correlation heat map of variables, cross-section data set, for Guatemala

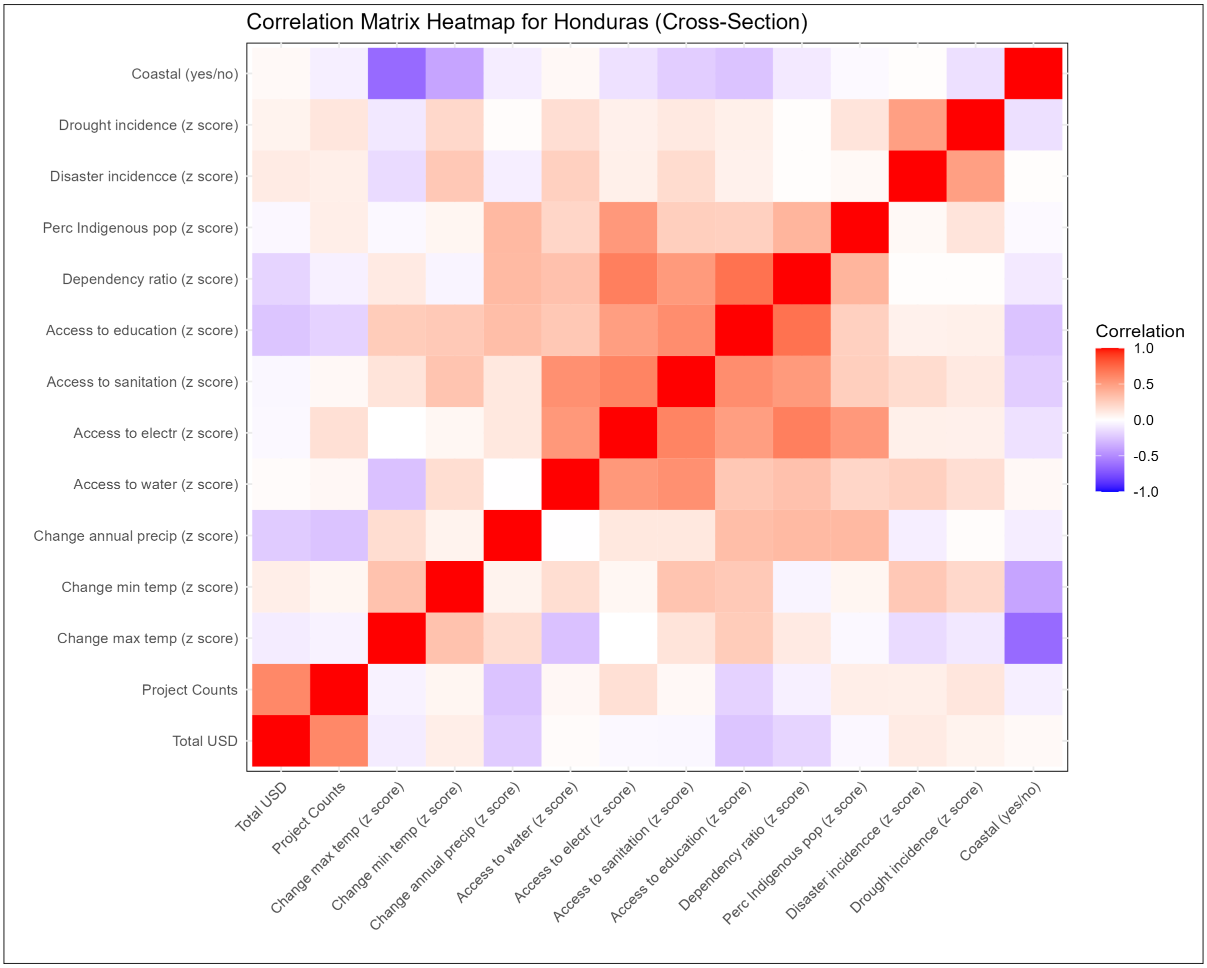

Figure A.4: Country-level correlation heat map of variables, cross-section data set, for Honduras

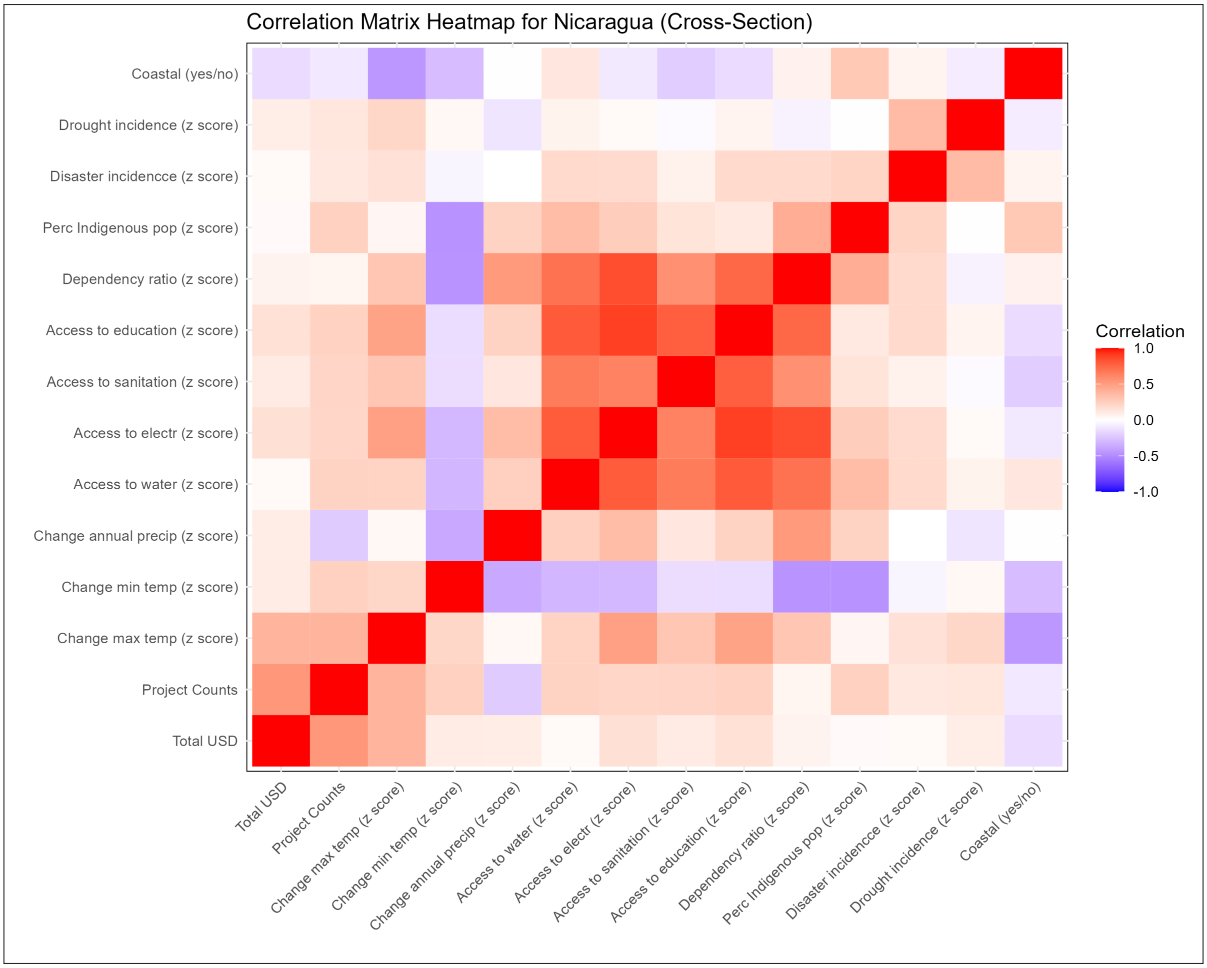

Figure A.5: Country-level correlation heat map of variables, cross-section data set, for Nicaragua

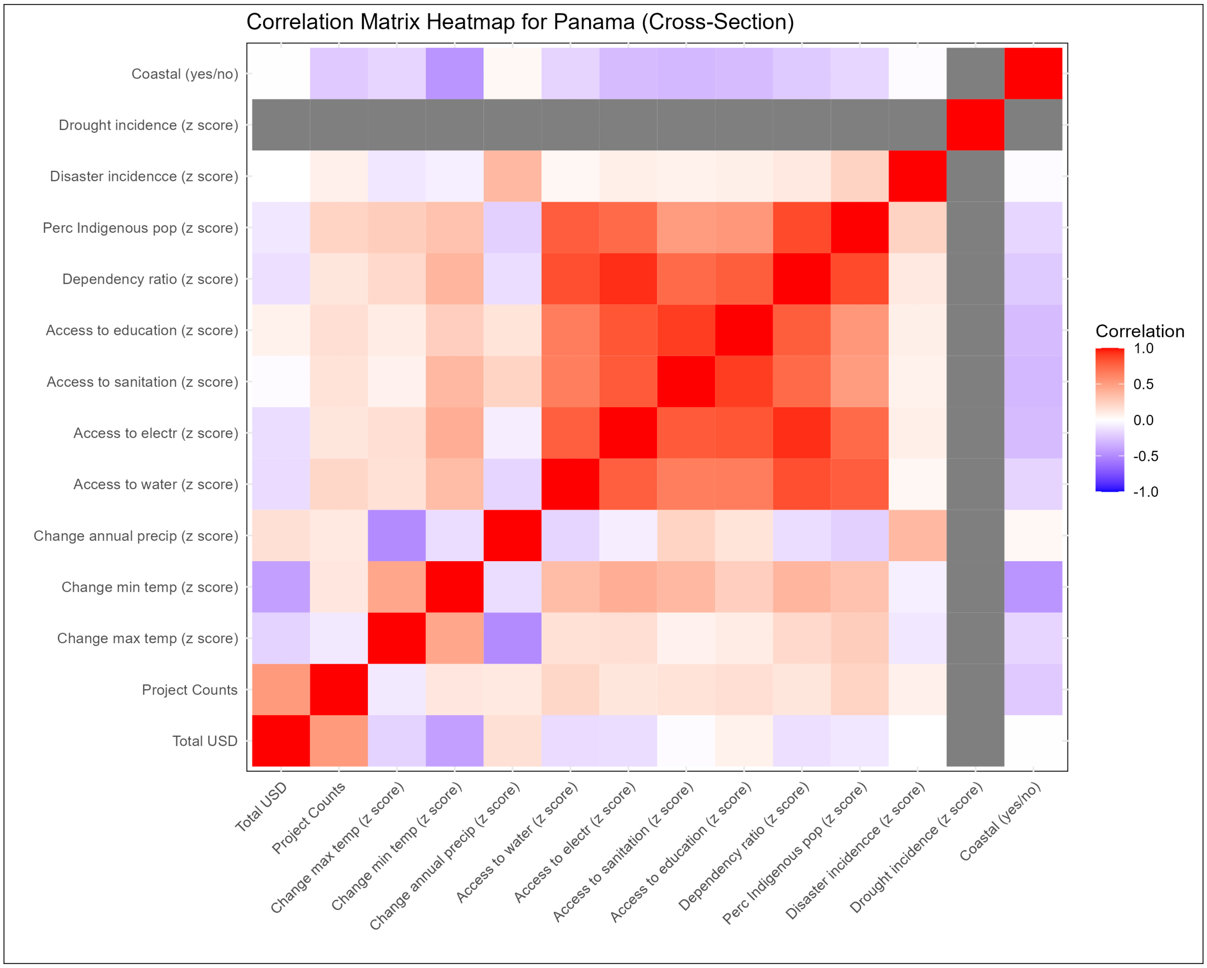

Figure A.6: Country-level correlation heat map of variables, cross-section data set, for Panama

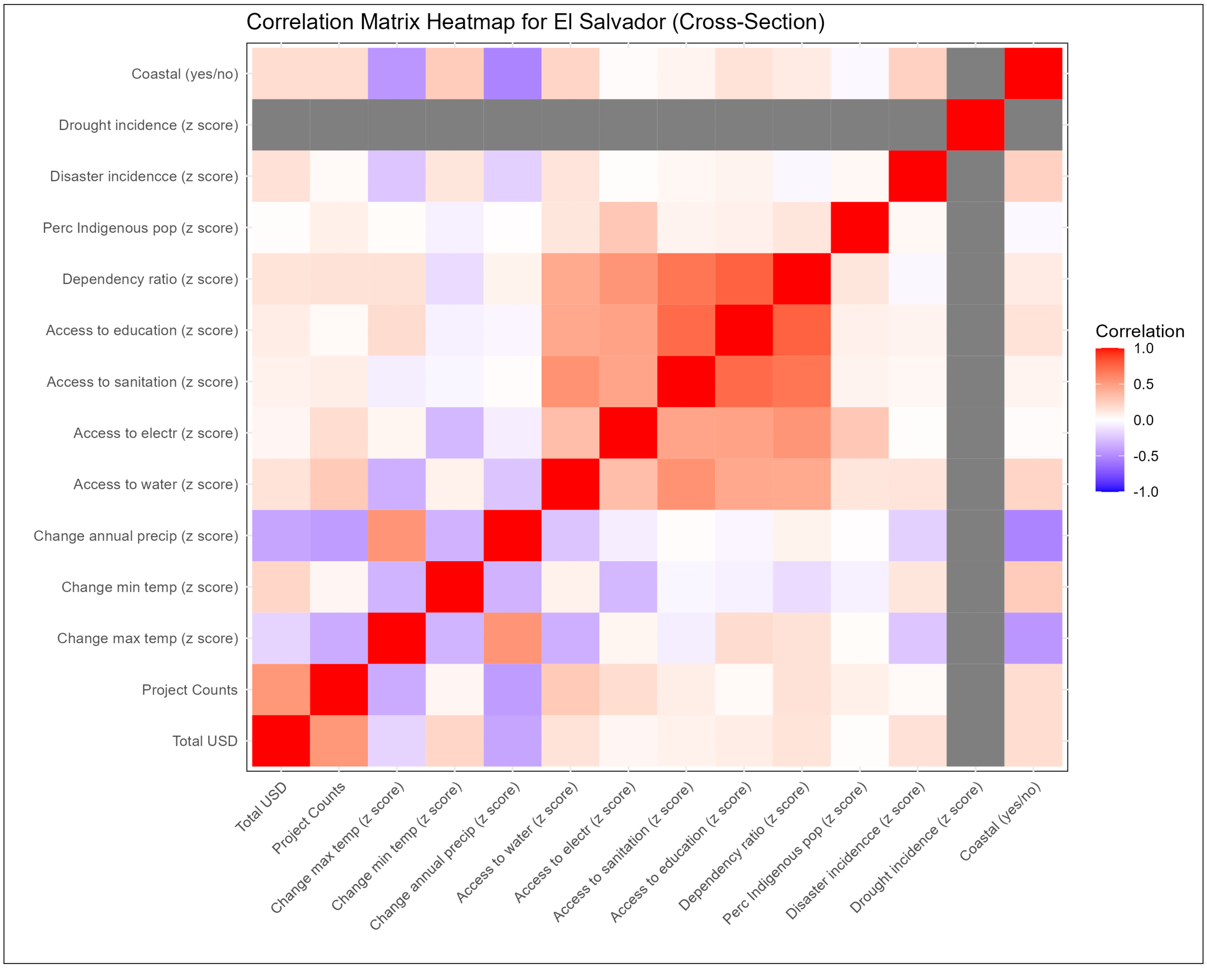

Figure A.7: Country-level correlation heat map of variables, cross-section data set, for El Salvador

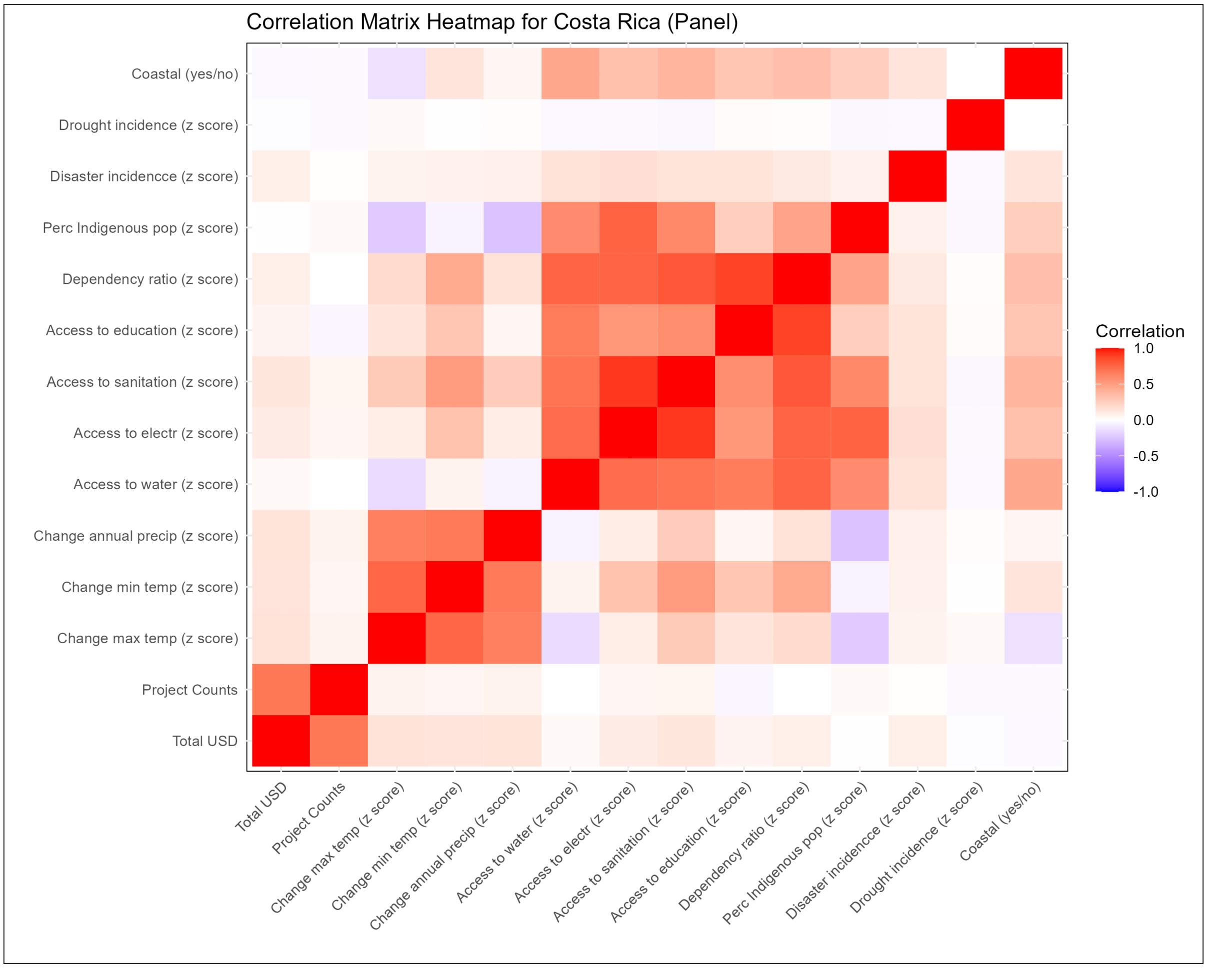

Figure A.8: Country-level correlation heat map of variables, panel data set, for Costa Rica

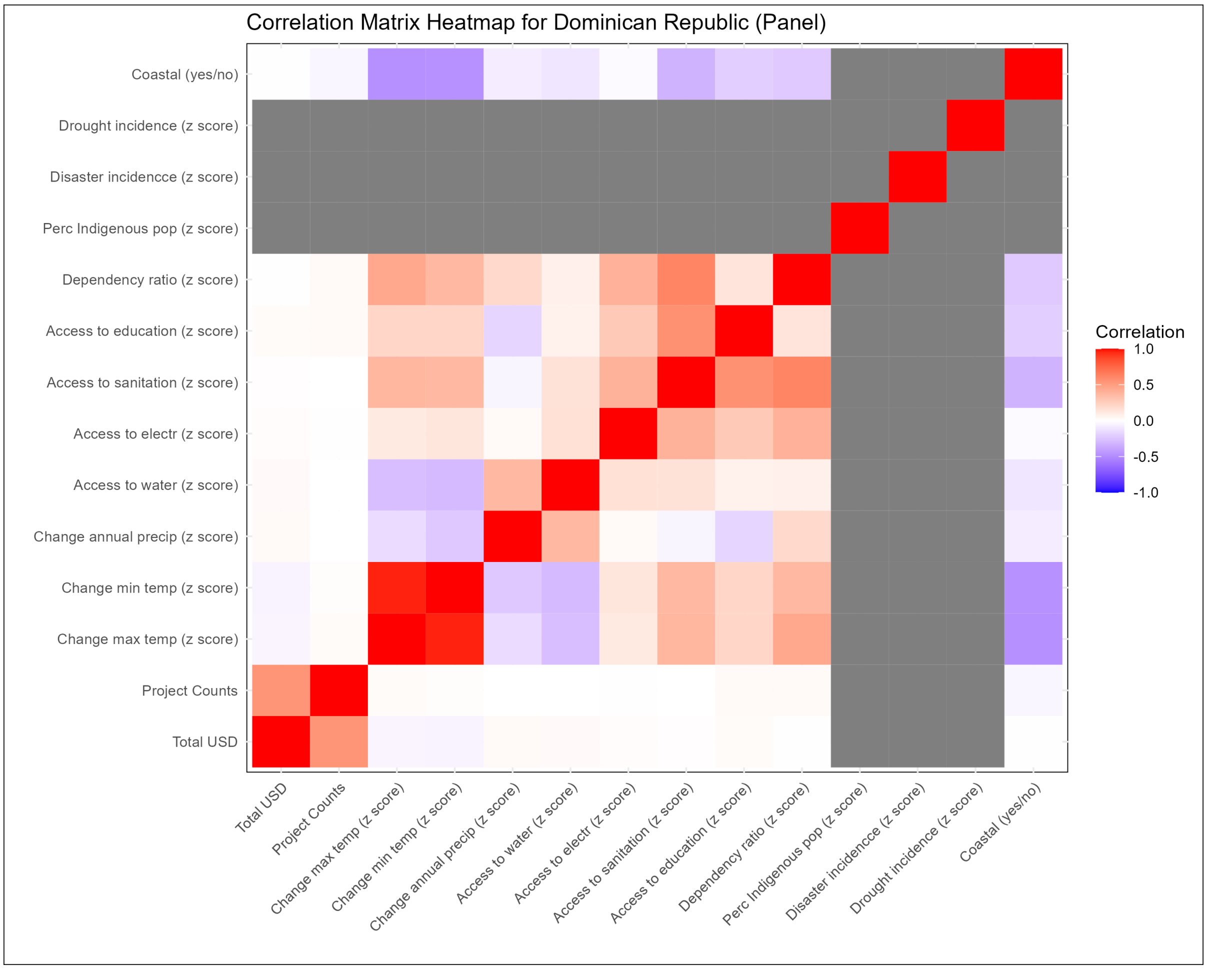

Figure A.9: Country-level correlation heat map of variables, panel data set, for the Dominican Republic

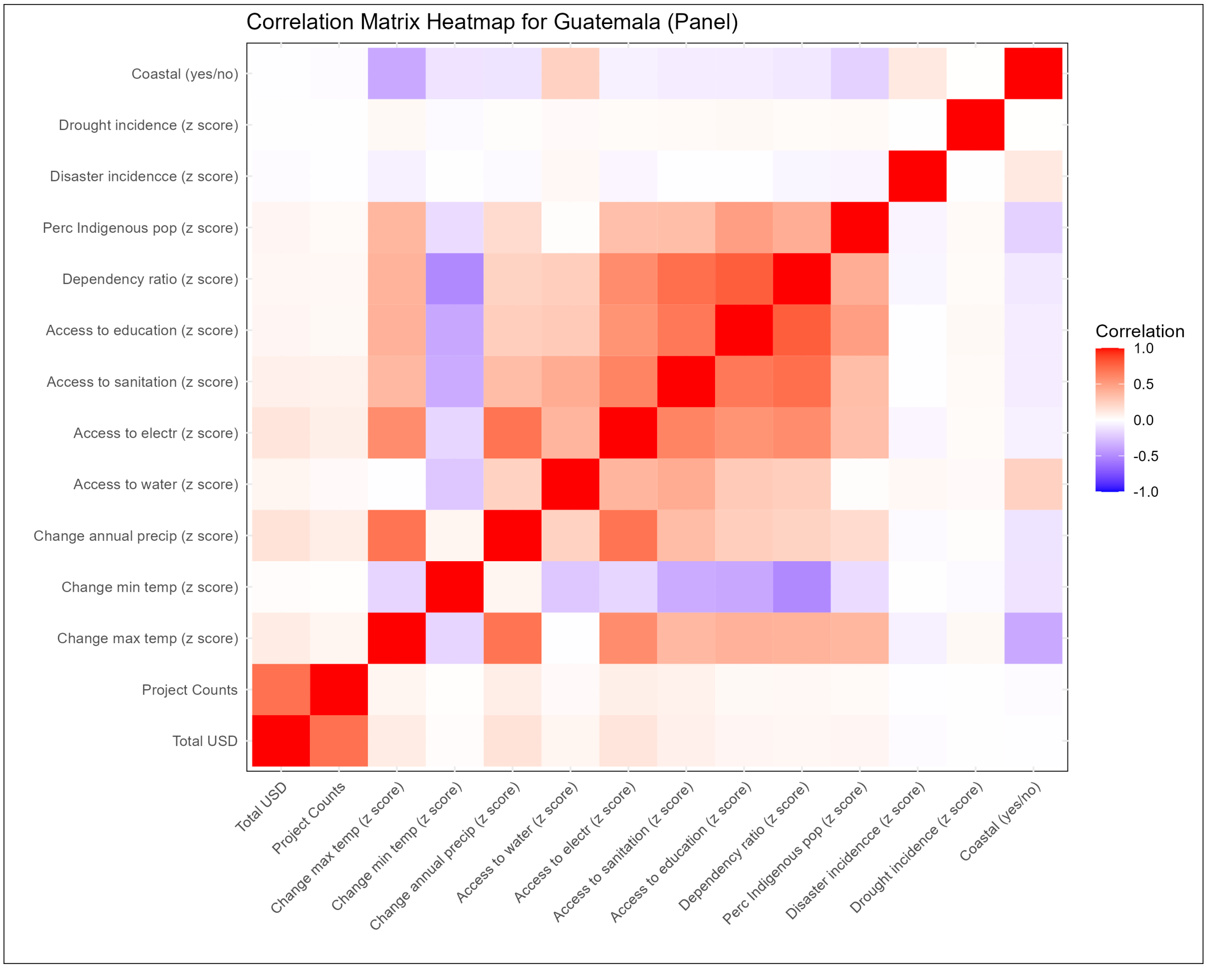

Figure A.10: Country-level correlation heat map of variables, panel data set, for Guatemala

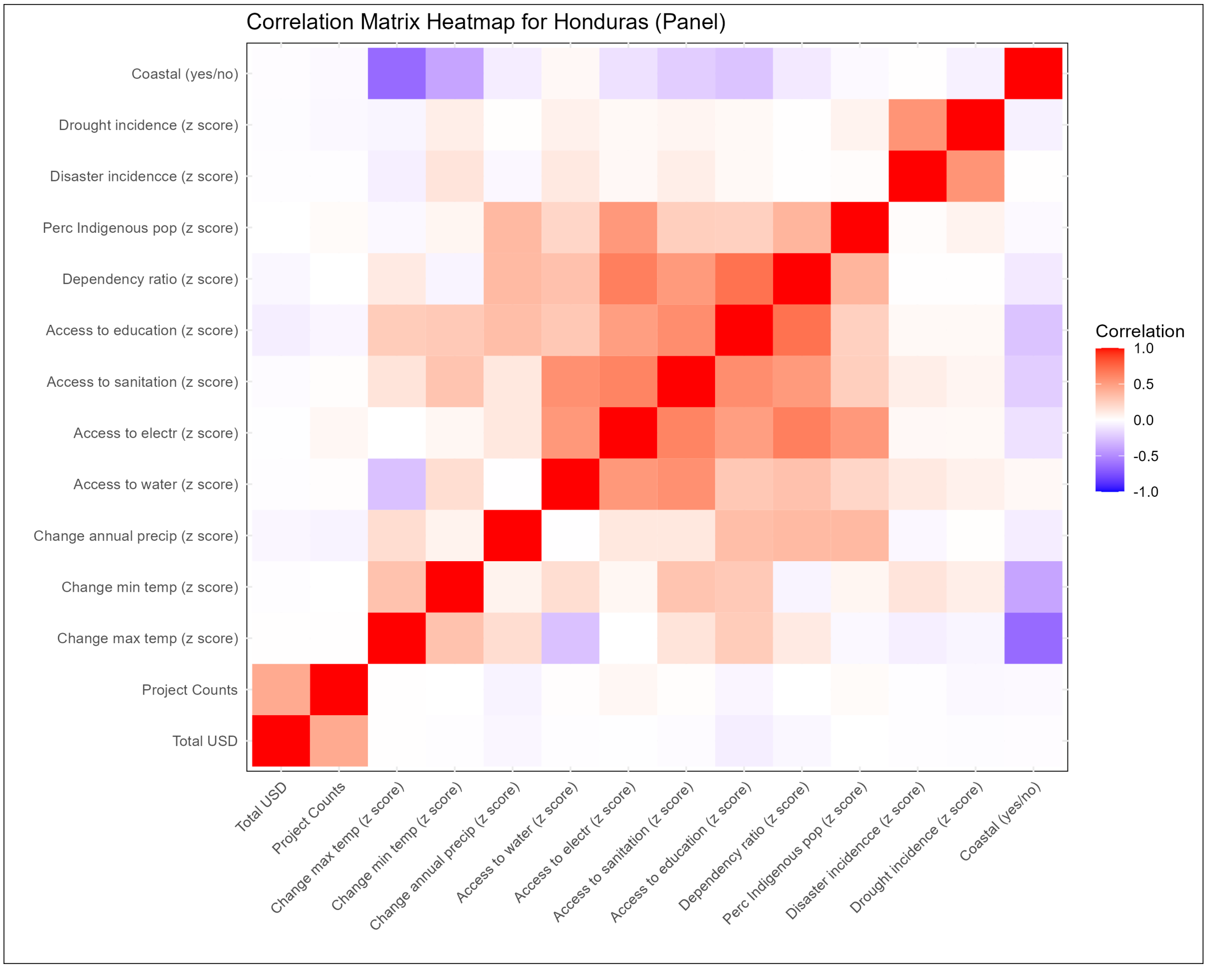

Figure A.11: Country-level correlation heat map of variables, panel data set, for Honduras

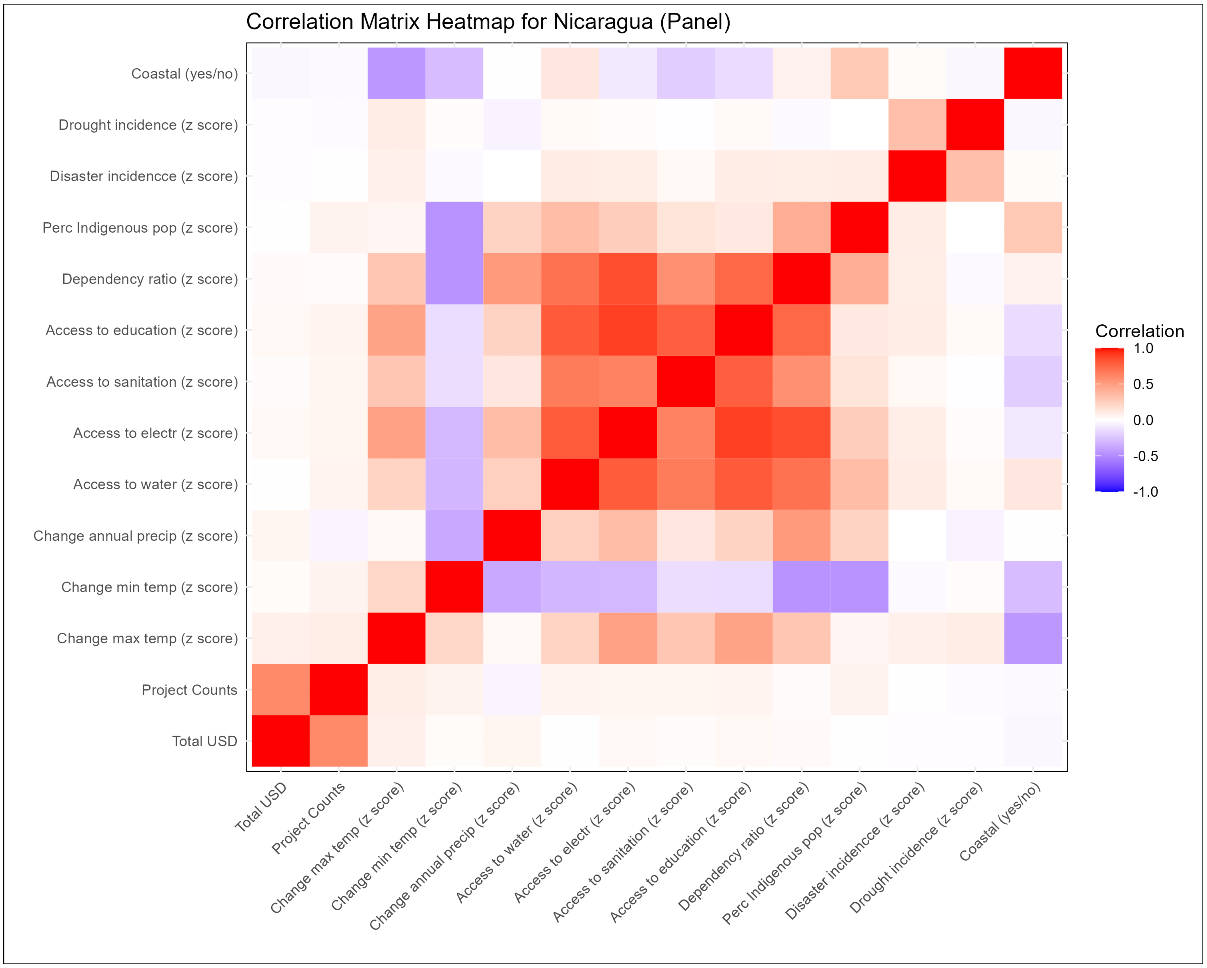

Figure A.12: Country-level correlation heat map of variables, panel data set, for Nicaragua

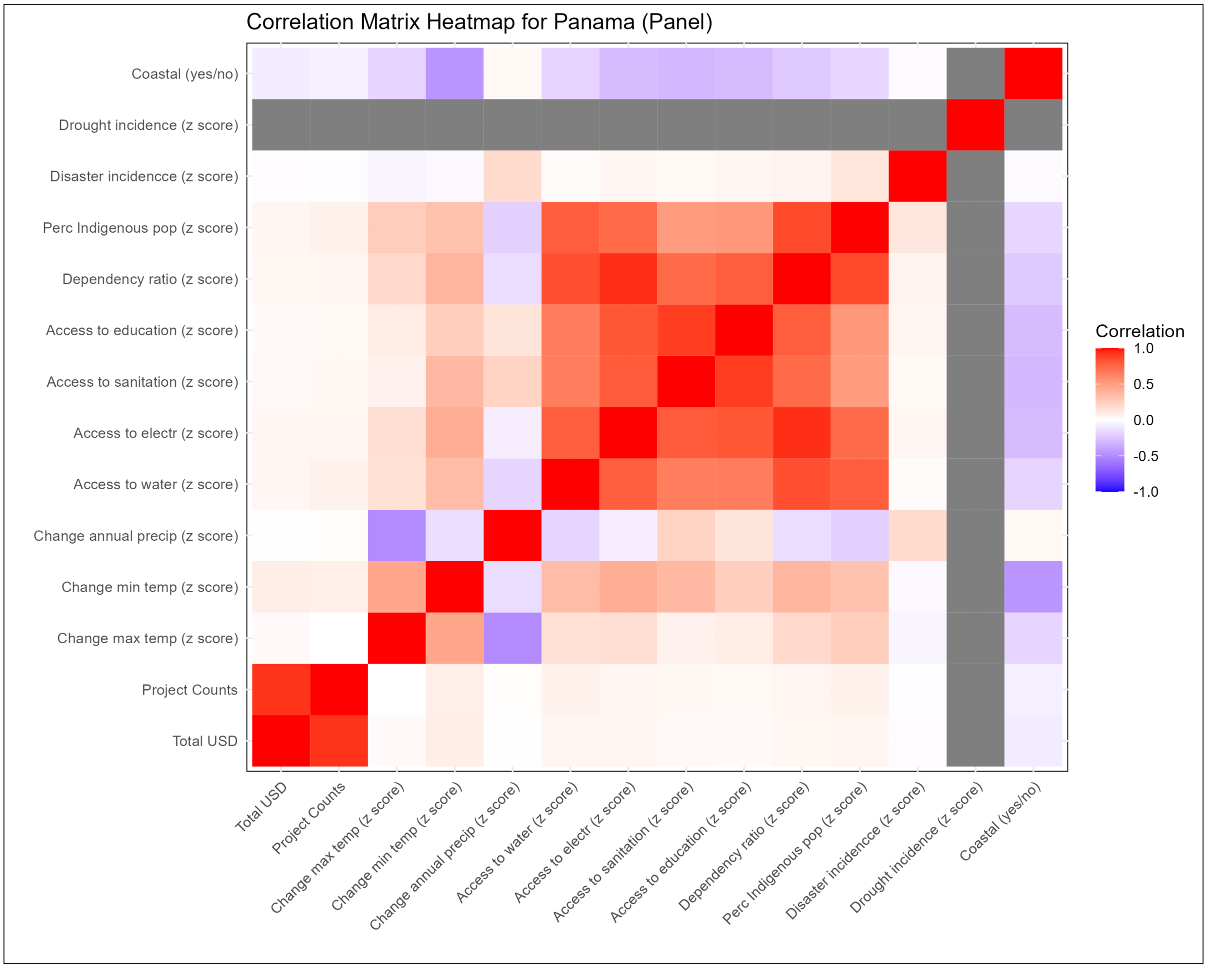

Figure A.13: Country-level correlation heat map of variables, panel data set, for Panama

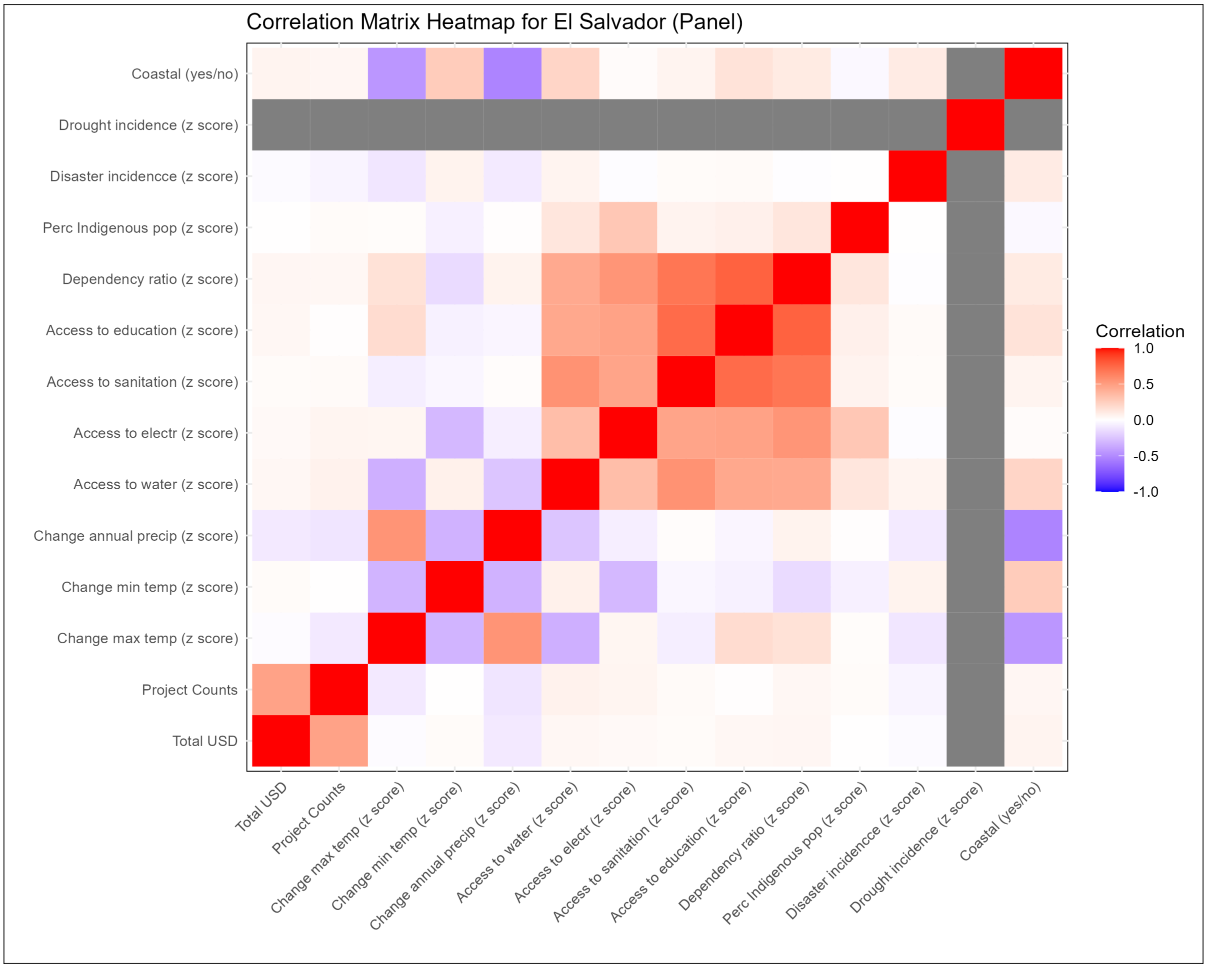

Figure A.14: Country-level correlation heat map of variables, panel data set, for El Salvador

A.4 Robustness of exposure index

In this section, I present regression analysis results using alternative climate change exposure measures to assess the main finding's robustness—that exposure does not predict adaptation funding allocations—against varied operationalizations and measurements.

Alternative measure of exposure: AR5 projections

In the main analysis, I used future exposure data from the IPCC 6th assessment report, which was presented in 2022. Because most of the funding data in this report precede that assessment report, I ran all analyses with the previous data from the AR5 report. Similar to the AR6 data, I downloaded bioclim data for RCP8.5 at 30-second resolution from the WorldClim database. The climate projection data are for the year 2050 and come from 17 different General Circulation Models (GCM). The historical climate data, also at a 30-second resolution, is for the period between 1970 and 2000 and was used as a baseline. I extracted average monthly values for all the municipalities in the sample for 3 indicators: maximum temperature of the warmest month (°C); minimum temperature of the coldest month (°C); and annual precipitation (mm). I subtracted the 2050 projected values from the baseline values to create a measure of climate change exposure along the 3 indicators. I calculated z-values for the 3 indicators and averaged them to form the climate change exposure index. Higher numbers correspond to higher vulnerability.

The outcomes of the base models in Table A.7, along with the results from the leave-one-out analyses presented in Tables A.8 through A.11, suggest that exposure, when defined through this alternative approach using AR5 data, does not predict the allocation of adaptation funding either.

Table A.7: Regression results for base models 1 - 4 where allocations are modeled as a function of Adaptive Capacity + Sensitivity + Exposure using exposure measures from AR5 (whereas the models in the main text use exposure measures from AR6)

	Model 1 AR5	**Model 2 AR5**	**Model 3 AR5**	**Model 4 AR5**
Dep. Var.:	log(Total USD+1)	Project Counts	log(Total USD+1)	Project Counts
Adap. Capacity	1.172 (0.616)	0.136* (0.049)	0.128*** (0.026)	0.009*** (0.002)
Sensitivity	0.247 (0.488)	0.071* (0.023)	0.004 (0.036)	0.002 (0.003)
Exposure	0.081 (0.971)	0.011 (0.128)	0.039 (0.030)	0.003 (0.003)
Fixed-Effects:				
Country	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes
S.E.: Clust. by:	Country	Country	Municipality	Municipality
Observations	1,358	1,358	19,012	19,012
R2	0.202	0.194	0.043	0.040
Within R2	0.029	0.034	0.002	0.002

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A.8: Leave-one-out robustness analysis for cross-sectional model 1, where allocations in current USD are modeled as a function of Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity). These models use exposure measures from AR5 (whereas the models in the main text use exposure measures from AR6).

	Model 1 without Adapt. Capacity	**Model 1 without Sensitivity**
Dependent Var.:	log(Total USD+1)	log(Total USD+1)
Sensitivity	1.275** (0.250)	
Exposure	0.116 (0.992)	0.093 (0.954)
Adaptive Capacity		1.288* (0.430)
Fixed-Effects:		
Country	Yes	Yes
S.E.: Clustered by:	Country	Country
Observations	1,358	1,358
R2	0.191	0.202
Within R2	0.015	0.029

Table A.9: Leave-one-out robustness analysis for cross-sectional model 2, where allocations in current USD are modeled as a function of Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity). These models use exposure measures from AR5 (whereas the models in the main text use exposure measures from AR6).

	Model 2 without Adapt. Capacity	**Model 2 without Sensitivity**
Dependent Var.:	log(Total USD+1)	log(Total USD+1)
Sensitivity	0.190** (0.040)	
Exposure	0.015 (0.131)	0.015 (0.126)
Adaptive Capacity		0.169** (0.045)
Fixed-Effects:		
Country	Yes	Yes
S.E.: Clustered by:	Country	Country
Observations	1,358	1,358
R2	0.184	0.193
Within R2	0.022	0.032

Table A.10: Leave-one-out robustness analysis for cross-sectional model 3, where allocations in project counts are modeled as a function of Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity). These models use exposure measures from AR5 (whereas the models in the main text use exposure measures from AR6).

	Model 3 without Adapt. Capacity	**Model 3 without Sensitivity**
Dependent Var.:	Project Counts	Project Counts
Sensitivity	0.116*** (0.026)	
Exposure	0.043 (0.030)	0.039 (0.030)
Adaptive Capacity		0.129*** (0.020)
Fixed-Effects:		
Country	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by:	Country	Country
Observations	19,012	19,012
R2	0.042	0.043
Within R2	0.001	0.002

Table A.11: Leave-one-out robustness analysis for cross-sectional model 4, where allocations in project counts are modeled as a function of Sensitivity + Exposure (leaving out Adaptive Capacity), and of Adaptive Capacity + Exposure (leaving out Sensitivity). These models use exposure measures from AR5 (whereas the models in the main text use exposure measures from AR6).

	Model 4 without Adapt. Capacity	**Model 4 without Sensitivity**
Dependent Var.:	Project Counts	Project Counts
Sensitivity	0.010*** (0.002)	
Exposure	0.003 (0.003)	0.003 (0.003)
Adaptive Capacity		0.010*** (0.002)
Fixed-Effects:		
Country	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by:	Country	Country
Observations	19,012	19,012
R2	0.039	0.040
Within R2	0.001	0.002

Alternative measure of exposure: Elevation and Sea Level Rise

In this analysis, I assess whether sea level rise (SLR) predicts the allocation of adaptation funds. I focused on coastal municipalities, assessing their risk based on elevation and projected SLR by 2050.

I used SLR projections from the IPCC's 6th Assessment Report from NASA's Physical Oceanography Distributed Active Archive Center. I selected the ssp585 medium confidence dataset for median SLR projections relative to the 1995-2014 baseline. For elevation data, I used the SRTM version 3 void-filled product from NASA Earth Data.

Using these data, I created two binary variables: one reflecting the risk of flooding based on elevation (municipalities with a higher percentage of their area under 5 meters than the average were considered at relative high risk) and the other based on projected SLR (municipalities with SLR projections above the mean were considered at relative high risk).

Table A.12 presents the outcomes of the regression analysis, indicating that vulnerability to sea level rise (SLR) does not predict the allocation of adaptation funding. This result is consistent with the core conclusion of this paper: exposure to climate change fails to predict how adaptation funds are distributed at the municipal level.

Table A.12: Regression results for sea level rise models 1 - 4 where allocations are modeled as a function of elevation vulnerability and sea level rise vulnerability.

	SLR Model 1	**SLR Model 2**	**SLR Model 3**	**SLR Model 4**
Dep. Var.:	log(Total USD+1)	Project Counts	log(Total USD+1)	Project Counts
Low Areas High Risk	-0.006 (0.857)	0.049 (0.148)	0.031 (0.085)	0.004 (0.007)
SLR High Risk	-0.767 (0.819)	-0.057 (0.167)	-0.096 (0.087)	-0.008 (0.007)
Fixed-Effects:				
Country	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes
S.E.: Clust. by:	Country	Country	Municipality	Municipality
Observations	1,358	1,358	19,012	19,012
R2	0.179	0.166	0.041	0.038
Within R2	0.001	0.000	0.000	0.000

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

A.5 Excluding one country at a time

To assess if the observed results are influenced by data from a single country as well as the validity of aggregating data across all countries, I conducted "leave one out" analyses leaving out one country at a time. I did this for a panel model where allocations are provided in current USD (Figure A.15) and for a panel model where allocations are models as Project counts as the dependent variable (Figure A.16). I found that omitting any single country did not result in statistically significant differences in the outcomes.

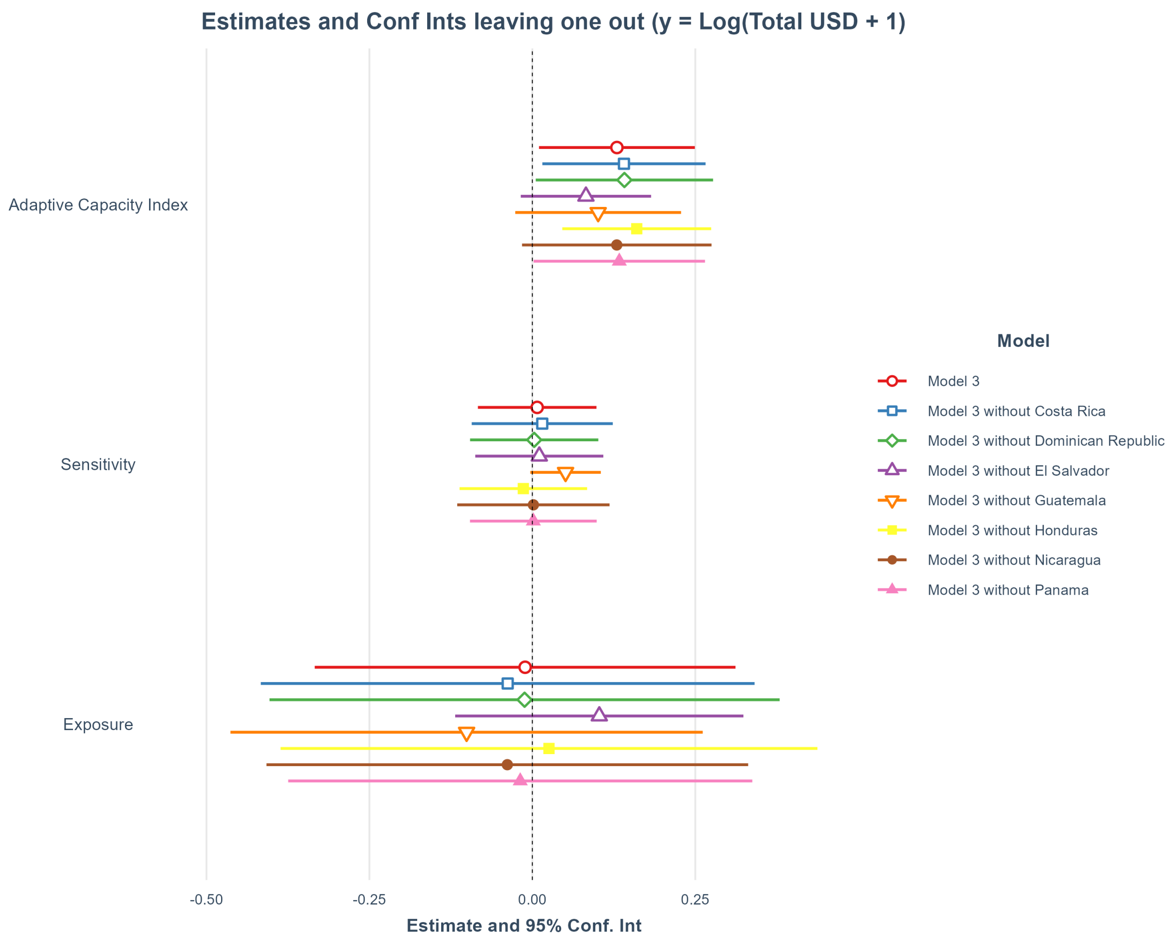

Figure A.15: Estimates and 95% confidence intervals for allocation amounts in USD, using model specifications that incorporate adaptive capacity, sensitivity, and exposure. Each color in the 'leave one out' analysis represents the exclusion of one country at a time

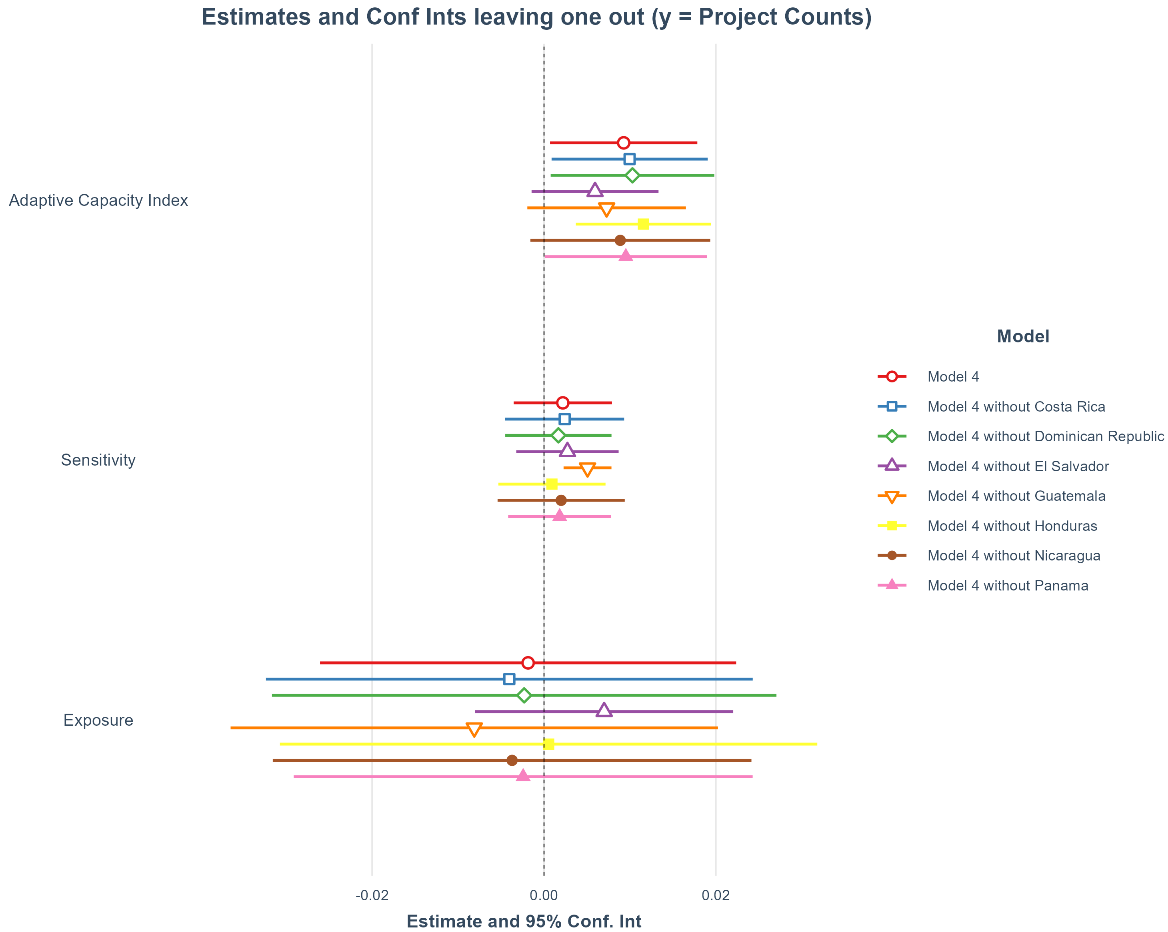

Figure A.16: Estimates and 95% confidence intervals for allocation amounts in project counts, using model specifications that incorporate adaptive capacity, sensitivity, and exposure. Each color in the 'leave one out' analysis represents the exclusion of one country at a time

Appendix B

Supplemental Information for Chapter 2 - Politics Biases the Allocation of International Funds for Climate Change Adaptation

B.1 Simple models

In the main text, we introduced four Regression Discontinuity Design (RDD) models that use fixed effects at both country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. The models are defined as follows:

- **Models 1 and 2** measure adaptation investments in monetary terms (in current USD), differing only in their polynomial specifications:
  - Model 1 uses a first-order polynomial.

  - Model 2 uses a second-order polynomial.

- **Models 3 and 4** evaluate adaptation investments by project counts, also differing in their polynomial specifications:
  - Model 3 uses a first-order polynomial.
  - Model 4 uses a second-order polynomial.

In this section, we present simple versions of these models that do not include fixed effects, covariates, or clustered standard errors. We include these additional elements in the complex models with the intention of increasing the precision of the estimates, but the effect of partisan alignment is still evident in these simpler models.

Simple Models 1 and 2

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.33		0.48	
Std. Err.	0.16		0.19	
z	2.12		2.47	
P>|z|	0.03		0.01	
95% C.I.	[0.03, 0.64]		[0.10, 0.86]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2793	2703	3515	3412
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	13.34	13.34	18.12	18.12
BW bias (b)	25.98	25.98	30.05	30.05
rho (h/b)	0.51	0.51	0.60	0.60
Unique Obs.	2929	1557	2929	1557

Table B.1: Robust RD Estimate for simple models 1 and 2

Simple Models 3 and 4

	(Model 3)		**(Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Robust Coef.	0.02		0.04	
Std. Err.	0.01		0.02	
z	1.79		2.40	
P>|z|	0.07		0.02	
95% C.I.	[-0.00, 0.05]		[0.01, 0.07]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2935	2862	3474	3379
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	14.29	14.29	17.79	17.79
BW bias (b)	26.97	26.97	29.70	29.70
rho (h/b)	0.53	0.53	0.60	0.60
Unique Obs.	2929	1557	2929	1557

Table B.2: Robust RD Estimate for models 3 and 4

B.2 Regression discontinuity models by country

The four RDD models discussed in the main text and in the prior section use pooled data from six countries: Costa Rica, the Dominican Republic, El Salvador, Guatemala, Honduras, and Panama. We chose this pooling strategy to increase the statistical power of the RDD analyses, given that these models focus on local effects around the cutoff. By aggregating data across multiple contexts, we increase the number of observations near the cutoff, allowing us to detect the presence of any discontinuities and to generalize the results across a broader set of conditions.

The trade-off in this pooled approach is that it ignores potentially important variations between countries. For example, it ignores whether the observed effect is predominantly driven by a single country or if certain countries demonstrate unique patterns.

In this section, we present the outputs of single-country RDD analyses. We start with ”simple” models without fixed effects, clustered SE, or covariates in (Tables B.3 - B.14) for each of the countries individually. We then present results for ”complex models” with the same specification as the models presented in the main section – fixed effects at the year level, SE clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure (Tables B.15 - B.20) for each of the countries individually.

While the analysis with the pooled the data from the six countries suggest a strong and statistically significant effect of partisan alignment on the allocation of adaptation funds at the municipal level, these disaggregated analyses by individual countries (Tables B.3 - B.20) yield varied results: positive effects in some countries, negative effects in others, and no statistically significant effects in most of them. In the simple models by country, only Guatemala (Tables B.9 - B.10) show a statistically significant effect of partisan alignment on project allocation in both current USD and project counts. In the complex models by country, only Honduras has a positive and statistically significant effect of partisan alignment on project allocation in current

USD (Table B.19). Guatemala has a statistically significant but negative effect for partisan alignment, and only for polynomial order 1 (Table B.18). Panama has a statistically significant but negative effect for partisan alignment for both polynomial order 1 and 2 (Table B.20).

These discrepancies in the single-country analyses suggest that there may be heterogeneous effects at the country level. However, it is not possible to determine this with certainty from this analysis alone because no clear pattern emerges, and results vary significantly across different specifications and levels of statistical significance. Recognizing that this may be related to insufficient power at individual country levels, we conducted a post-hoc power analysis. The objective was to determine the sample size needed in each country to detect an effect of similar size and statistical significance to that of the pooled data. The results (Table B.21) suggest that in most countries, the actual sample sizes are significantly lower than the required sample sizes, leading to insufficient power to detect a statistically significant effect. This is due both to the smaller number of observations per country and to the reduced number of observations around the cutoff in the regression discontinuity design.

B.2.1 Simple Regression Discontinuity models by country

Costa Rica

	(Costa Rica Model 1)		(Costa Rica Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	-0.58		-0.27	
Std. Err.	0.68		0.80	
z	-0.85		-0.34	
P>|z|	0.40		0.74	
95% C.I.	[-1.92, 0.76]		[-1.84, 1.30]	
Number of Total Obs.	891		891	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	615	276	615	276
Eff. Number of Obs.	123	135	180	171
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	15.18	15.18	18.60	18.60
BW bias (b)	25.52	25.52	26.06	26.06
rho (h/b)	0.59	0.59	0.71	0.71
Unique Obs.	249	75	249	75

Table B.3: Robust RD Estimate for Costa Rica simple models 1 and 2. No covariates, fixed effects, or clustered SE. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Costa Rica Model 3)		**(Costa Rica Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Robust Coef.	-0.08		-0.05	
Std. Err.	0.07		0.08	
z	-1.15		-0.63	
P>|z|	0.25		0.53	
95% C.I.	[-0.21, 0.05]		[-0.21, 0.11]	
Number of Total Obs.	891		891	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	615	276	615	276
Eff. Number of Obs.	147	155	211	179
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	16.34	16.34	20.84	20.84
BW bias (b)	25.65	25.65	27.06	27.06
rho (h/b)	0.64	0.64	0.77	0.77
Unique Obs.	249	75	249	75

Table B.4: Robust RD Estimate for Costa Rica simple models 3 and 4. No covariates, fixed effects, or clustered SE. Outcome in project counts. Model 3 uses 1st order polynomial and model 4 uses 2nd order polynomial.

Dominican Republic

	(Dom. Rep. Model 1)		**(Dom. Rep. Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.01		0.04	
Std. Err.	0.02		0.07	
z	0.53		0.54	
P>|z|	0.60		0.59	
95% C.I.	[-0.02, 0.04]		[-0.10, 0.17]	
Number of Total Obs.	1621		1621	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	599	1022	599	1022
Eff. Number of Obs.	262	251	391	427
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	4.47	4.47	8.40	8.40
BW bias (b)	11.22	11.22	17.93	17.93
rho (h/b)	0.40	0.40	0.47	0.47
Unique Obs.	178	267	178	267

Table B.5: Robust RD Estimate for Dominican Republic simple models 1 and 2. No covariates, fixed effects, or clustered SE. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Dom. Rep. Model 3)		**(Dom. Rep. Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Robust Coef.	0.00		0.01	
Std. Err.	0.00		0.01	
z	0.67		0.80	
P>|z|	0.50		0.42	
95% C.I.	[-0.01, 0.01]		[-0.01, 0.02]	
Number of Total Obs.	1621		1621	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	599	1022	599	1022
Eff. Number of Obs.	293	287	396	464
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	5.23	5.23	9.04	9.04
BW bias (b)	10.26	10.26	20.55	20.55
rho (h/b)	0.51	0.51	0.44	0.44
Unique Obs.	178	267	178	267

Table B.6: Robust RD Estimate for Dominican Republic simple models 3 and 4. No covariates, fixed effects, or clustered SE. Outcome in project counts. Model 3 uses 1st order polynomial and model 4 uses 2nd order polynomial.

El Salvador

	(El Salvador Model 1)		**(El Salvador Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	-0.02		0.57	
Std. Err.	0.41		0.56	
z	-0.04		1.01	
P>|z|	0.97		0.31	
95% C.I.	[-0.83, 0.80]		[-0.53, 1.67]	
Number of Total Obs.	2882		2882	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	2033	849	2033	849
Eff. Number of Obs.	898	669	922	679
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	20.09	20.09	20.80	20.80
BW bias (b)	35.51	35.51	31.39	31.39
rho (h/b)	0.57	0.57	0.66	0.66
Unique Obs.	934	367	934	367

Table B.7: Robust RD Estimate for El Salvador simple models 1 and 2. No covariates, fixed effects, or clustered SE. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(El Salvador Model 3)		**(El Salvador Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Robust Coef.	0.00		0.04	
Std. Err.	0.03		0.05	
z	0.07		0.96	
P>|z|	0.94		0.34	
95% C.I.	[-0.07, 0.07]		[-0.05, 0.13]	
Number of Total Obs.	2882		2882	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	2033	849	2033	849
Eff. Number of Obs.	856	642	919	679
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	18.94	18.94	20.73	20.73
BW bias (b)	32.62	32.62	31.18	31.18
rho (h/b)	0.58	0.58	0.66	0.66
Unique Obs.	934	367	934	367

Table B.8: Robust RD Estimate for El Salvador simple models 3 and 4. No covariates, fixed effects, or clustered SE. Outcome in project counts. Model 3 uses 1st order polynomial and model 4 uses 2nd order polynomial.

Guatemala

	(Guatemala Model 1)		**(Guatemala Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.74		0.80	
Std. Err.	0.34		0.37	
z	2.20		2.15	
P>|z|	0.03		0.03	
95% C.I.	[0.08, 1.40]		[0.07, 1.52]	
Number of Total Obs.	3662		3662	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	3027	635	3027	635
Eff. Number of Obs.	533	340	757	429
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.02	11.02	14.81	14.81
BW bias (b)	16.42	16.42	21.69	21.69
rho (h/b)	0.67	0.67	0.68	0.68
Unique Obs.	1081	250	1081	250

Table B.9: Robust RD Estimate for Guatemala simple models 1 and 2. No covariates, fixed effects, or clustered SE. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Guatemala Model 3)		**(Guatemala Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Robust Coef.	0.06		0.06	
Std. Err.	0.03		0.03	
z	2.06		2.00	
P>|z|	0.04		0.05	
95% C.I.	[0.00, 0.11]		[0.00, 0.12]	
Number of Total Obs.	3662		3662	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	3027	635	3027	635
Eff. Number of Obs.	533	340	717	399
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.01	11.01	13.98	13.98
BW bias (b)	16.66	16.66	20.65	20.65
rho (h/b)	0.66	0.66	0.68	0.68
Unique Obs.	1081	250	1081	250

Table B.10: Robust RD Estimate for Guatemala simple models 3 and 4. No covariates, fixed effects, or clustered SE. Outcome in project counts. Model 3 uses 1st order polynomial and model 4 uses 2nd order polynomial.

Honduras

	(Honduras Model 1)		(Honduras Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.38		0.73	
Std. Err.	0.32		0.44	
z	1.18		1.67	
P>|z|	0.24		0.10	
95% C.I.	[-0.25, 1.02]		[-0.13, 1.58]	
Number of Total Obs.	3168		3168	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	1220	1948	1220	1948
Eff. Number of Obs.	830	1104	869	1153
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	18.25	18.25	19.62	19.62
BW bias (b)	29.97	29.97	29.35	29.35
rho (h/b)	0.61	0.61	0.67	0.67
Unique Obs.	335	529	335	529

Table B.11: Robust RD Estimate for Honduras simple models 1 and 2. No covariates, fixed effects, or clustered SE. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Honduras Model 3)		**(Honduras Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Robust Coef.	0.03		0.05	
Std. Err.	0.02		0.03	
z	1.15		1.56	
P>|z|	0.25		0.12	
95% C.I.	[-0.02, 0.07]		[-0.01, 0.12]	
Number of Total Obs.	3168		3168	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	1220	1948	1220	1948
Eff. Number of Obs.	869	1157	891	1194
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	19.74	19.74	20.62	20.62
BW bias (b)	33.75	33.75	30.50	30.50
rho (h/b)	0.58	0.58	0.68	0.68
Unique Obs.	335	529	335	529

Table B.12: Robust RD Estimate for Honduras simple models 3 and 4. No covariates, fixed effects, or clustered SE. Outcome in project counts. Model 3 uses 1st order polynomial and model 4 uses 2nd order polynomial.

Panama

	(Panama Model 1)		(Panama Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	-0.87		-1.09	
Std. Err.	0.71		1.16	
z	-1.23		-0.94	
P>|z|	0.22		0.35	
95% C.I.	[-2.25, 0.52]		[-3.38, 1.19]	
Number of Total Obs.	814		814	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	594	220	594	220
Eff. Number of Obs.	136	141	144	148
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	9.54	9.54	9.77	9.77
BW bias (b)	15.14	15.14	13.33	13.33
rho (h/b)	0.63	0.63	0.73	0.73
Unique Obs.	153	69	153	69

Table B.13: Robust RD Estimate for Panama simple models 1 and 2. No covariates, fixed effects, or clustered SE. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Panama Model 1)		**(Panama Model 2)**	
Dependent Var.:	Project Counts		Project Counts	
Robust Coef.	-0.07		-0.09	
Std. Err.	0.06		0.09	
z	-1.20		-0.95	
P>|z|	0.23		0.34	
95% C.I.	[-0.18, 0.04]		[-0.27, 0.09]	
Number of Total Obs.	814		814	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
	Control	Treated	Control	Treated
Number of Obs.	594	220	594	220
Eff. Number of Obs.	136	146	144	146
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	9.59	9.59	9.76	9.76
BW bias (b)	15.65	15.65	13.34	13.34
rho (h/b)	0.61	0.61	0.73	0.73
Unique Obs.	153	69	153	69

Table B.14: Robust RD Estimate for Panama simple models 3 and 4. No covariates, fixed effects, or clustered SE. Outcome in project counts. Model 3 uses 1st order polynomial and model 4 uses 2nd order polynomial.

Complex Regression Discontinuity models by country

Costa Rica

	(Costa Rica Model 1)		(Costa Rica Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.08		0.16	
Std. Err.	0.32		0.24	
z	0.26		0.67	
P>|z|	0.79		0.51	
95% C.I.	[-0.54, 0.70]		[-0.32, 0.64]	
Number of Total Obs.	891		891	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	615	276	615	276
Eff. Number of Obs.	92	111	149	155
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.79	11.79	16.81	16.81
BW bias (b)	25.24	25.24	25.14	25.14
rho (h/b)	0.47	0.47	0.67	0.67
Unique Obs.	249	75	249	75

Table B.15: Robust RD Estimate for Costa Rica complex models 1 and 2. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

Dominican Republic

	(Dom. Rep. Model 1)		**(Dom. Rep. Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.00		0.00	
Std. Err.	0.00		0.00	
z	NaN		18741369275239.71	
P>|z|	NaN		0.00	
95% C.I.	[0.00, 0.00]		[0.00, 0.00]	
Number of Total Obs.	1621		1621	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	599	1022	599	1022
Eff. Number of Obs.	238	202	191	173
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	3.81	3.81	3.26	3.26
BW bias (b)	3.86	3.86	6.50	6.50
rho (h/b)	0.99	0.99	0.50	0.50
Unique Obs.	178	267	178	267

Table B.16: Robust RD Estimate for Dominican Republic complex models 1 and 2. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

El Salvador

	(SLV Model 1)		**(SLV Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.13		0.45	
Std. Err.	0.30		0.54	
z	0.44		0.83	
P>|z|	0.66		0.41	
95% C.I.	[-0.45, 0.71]		[-0.61, 1.51]	
Number of Total Obs.	2882		2882	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	2033	849	2033	849
Eff. Number of Obs.	866	651	820	628
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	19.36	19.36	18.25	18.25
BW bias (b)	34.43	34.43	25.15	25.15
rho (h/b)	0.56	0.56	0.73	0.73
Unique Obs.	934	367	934	367

Table B.17: Robust RD Estimate for El Salvador complex models 1 and 2. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

Guatemala

	(GUA Model 1)		**(GUA Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	-8.64		0.87	
Std. Err.	1.73		0.80	
z	-5.00		1.09	
P>|z|	0.00		0.28	
95% C.I.	[-12.03, -5.26]		[-0.69, 2.43]	
Number of Total Obs.	3662		3662	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	3027	635	3027	635
Eff. Number of Obs.	303	224	557	358
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	6.10	6.10	11.60	11.60
BW bias (b)	11.63	11.63	19.03	19.03
rho (h/b)	0.52	0.52	0.61	0.61
Unique Obs.	1081	250	1081	250

Table B.18: Robust RD Estimate for Guatemala complex models 1 and 2. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

Honduras

	(HND Model 1)		(HND Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.20		0.66	
Std. Err.	0.04		0.10	
z	4.40		6.56	
P>|z|	0.00		0.00	
95% C.I.	[0.11, 0.28]		[0.46, 0.85]	
Number of Total Obs.	3168		3168	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	1220	1948	1220	1948
Eff. Number of Obs.	961	1353	621	740
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	23.98	23.98	11.67	11.67
BW bias (b)	35.92	35.92	30.12	30.12
rho (h/b)	0.67	0.67	0.39	0.39
Unique Obs.	335	529	335	529

Table B.19: Robust RD Estimate for Honduras complex models 1 and 2. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

Panama

	(PAN Model 1)		(PAN Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	-1.67		-2.31	
Std. Err.	0.31		0.60	
z	-5.30		-3.86	
P>|z|	0.00		0.00	
95% C.I.	[-2.29, -1.05]		[-3.48, -1.14]	
Number of Total Obs.	814		814	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	594	220	594	220
Eff. Number of Obs.	98	93	113	116
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	6.42	6.42	7.27	7.27
BW bias (b)	14.44	14.44	11.74	11.74
rho (h/b)	0.44	0.44	0.62	0.62
Unique Obs.	153	69	153	69

Table B.20: Robust RD Estimate for Panama complex models 1 and 2. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

Table B.21: Summary results of the power analysis performed for each country included in the study. The columns display the calculated effect size (Cohen's d), the required sample size per group to achieve 80% power at a 5% significance level, and the actual sample sizes in the control and treated groups in each country. These results suggest that in most countries, the actual sample sizes are significantly lower than the required sample sizes, leading to insufficient power to detect a statistically significant effect. This is primarily due to the limited number of observations around the cutoff in the regression discontinuity design.

Country	**Effect Size (Cohen's d)**	**Required Group Size**	**Actual Control Group Size**	**Actual Treated Group Size**
Costa Rica	0.1008	1546.76	92	111
Dominican Republic	0.3147	159.51	238	202
El Salvador	0.0918	1865.09	866	651
Guatemala	0.1634	588.99	303	224
Honduras	0.0962	1698.78	961	1353
Panama	0.1450	747.57	98	93

B.3 Variations in funding mechanisms and local partners

The models discussed above do not distinguish between the funding mechanisms for adaptation projects (e.g., loans, grants, etc.) or the identity of the funding partner in the recipient country (e.g., non-profits vs. government agencies). Recognizing that the effects of partisan alignment on projects may vary depending on the funding mechanism or the type of on-site partners, this section explores heterogeneous effects by both funding mechanism and on-site partners.

We categorize funding instruments into three types: grants, non-grants, and unknown mechanisms. Additionally, we differentiate partners into two categories: state actors and non-state actors. We then split the sample to reflect this categorization; for instance, if Municipality A received $10,000 in 2018, with $5,000 from a grant and $5,000 from a non-grant source, we categorize the municipality as having received only $5,000 that year in the first model below, corresponding to the grant portion of the funding.

All the models specify the outcome in current USD, include fixed effects at the country and year level, standard errors clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. We present results for models that use a 1st order polynomial and a second order polynomial.

We find a statistically significant effect of partisan alignment on the allocation of projects funded through mechanisms other than grants (Tables B.23 and B.24). We see this effect in projects categorized as non-grant funded and in those with no specified funding mechanism, which covers projects where the funding mechanism could not be determined from the project documents. Conversely, we do not observe a statistically significant effect of partisan alignment on the allocation of grant-funded projects (Table B.22). Additionally, there is a statistically significant effect of partisan alignment on the allocation of projects involving non-state actors as country partners (Table B.26), whereas no such effect is observed when the country partners are state actors (Table B.25). These results are preliminary and were not part of the original research design, hence they are not discussed in depth in the main text due to their more exploratory nature. Nonetheless, these results suggest promising avenues for future research of heterogeneous effects. Normatively, projects involving non-state actors as partners are expected to be less susceptible to clientelistic distribution. However, anecdotal evidence from field interviews often emphasized that ”everything is political,” even when the partner was an NGO. This implies that mechanisms designed by international donors to ensure more direct access might not be sufficient to withstand clientelism. These findings highlight the importance of additional research to understand the political dynamics of climate change funding allocations subnationally.

	(Model 1)		(Model 2)	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.12		0.18	
Std. Err.	0.16		0.18	
z	0.71		0.97	
P>|z|	0.48		0.33	
95% C.I.	[-0.21, 0.44]		[-0.18, 0.54]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2834	2768	3630	3469
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	13.66	13.66	18.76	18.76
BW bias (b)	23.21	23.21	25.05	25.05
rho (h/b)	0.59	0.59	0.75	0.75
Unique Obs.	2929	1557	2929	1557

Table B.22: Robust RD Estimate for subsample of grant-funded projects. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.06		0.16	
Std. Err.	0.08		0.08	
z	0.71		1.90	
P>|z|	0.48		0.06	
95% C.I.	[-0.10, 0.22]		[-0.00, 0.32]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	3172	3094	3132	3068
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	15.70	15.70	15.57	15.57
BW bias (b)	23.57	23.57	25.64	25.64
rho (h/b)	0.67	0.67	0.61	0.61
Unique Obs.	2929	1557	2929	1557

Table B.23: Robust RD Estimate for subsample of non-grant-funded projects. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.06		0.05	
Std. Err.	0.02		0.02	
z	2.63		2.14	
P>|z|	0.01		0.03	
95% C.I.	[0.01, 0.10]		[0.00, 0.10]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2351	2295	3633	3469
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	10.87	10.87	18.77	18.77
BW bias (b)	20.03	20.03	32.33	32.33
rho (h/b)	0.54	0.54	0.58	0.58
Unique Obs.	2929	1557	2929	1557

Table B.24: Robust RD Estimate for subsample of projects with no specified funding mechanism. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

Split sample by type State vs. non-State actor

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	-0.03		-0.06	
Std. Err.	0.09		0.10	
z	-0.29		-0.67	
P>|z|	0.77		0.50	
95% C.I.	[-0.21, 0.15]		[-0.25, 0.12]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2922	2856	4597	4067
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	14.23	14.23	25.85	25.85
BW bias (b)	21.17	21.17	35.69	35.69
rho (h/b)	0.67	0.67	0.72	0.72
Unique Obs.	2929	1557	2929	1557

Table B.25: Robust RD Estimate for subsample of projects where the partner is a state actor. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Robust Coef.	0.29		0.36	
Std. Err.	0.14		0.15	
z	2.03		2.46	
P>|z|	0.04		0.01	
95% C.I.	[0.01, 0.57]		[0.07, 0.65]	
Number of Total Obs.	13038		13038	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Fixed-Effects	by: Year		by: Year	
S.E.: Clustered	by: Electoral Cycle		by: Electoral Cycle	
	Control	Treated	Control	Treated
Number of Obs.	8088	4950	8088	4950
Eff. Number of Obs.	2527	2499	3299	3205
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.98	11.98	16.54	16.54
BW bias (b)	21.25	21.25	23.85	23.85
rho (h/b)	0.56	0.56	0.69	0.69
Unique Obs.	2929	1557	2929	1557

Table B.26: Robust RD Estimate for subsample of projects where the partner is not a state actor. Fixed effects at country and year levels, standard errors (SE) clustered at the electoral level, and three covariates: adaptive capacity, sensitivity, and exposure. Outcome in current USD. Model 1 uses 1st order polynomial and model 2 uses 2nd order polynomial.

B.4 Sensitivity to bandwidth selection

In this section, we explore the effect of varying the bandwidth selection (i.e., the window around the cutoff from which observations are selected) on the robust estimate and its corresponding 95% confidence interval (CI). We manually adjust the bandwidth from 1 to 30 in 1-unit increments and show the results in coefficient plots for each one of the models.

In our context, the bandwidth refers to the value of the voting margin, where values closer to 0 indicate tighter election outcomes. For instance, a bandwidth of -10 and 10 effectively means that we have restricted our sample to observations where the voting margin was relatively narrow, and the candidate aligned with the president's party won or lost by 10% or less.

By varying the bandwidth, we aim to understand how the precision and magnitude of the estimated treatment effect change as we include more or fewer observations around the cutoff. This sensitivity analysis assists us in grasping the extent to which our results depend on the choice of bandwidth.

Figure B.1 illustrates that for Model 1, bandwidth selections ranging from 9 to 15 yield robust estimates that are significantly different from 0. Similarly, for Model 2 (Figure B.2), the robust estimates are obtained with bandwidths between 13 and 26. Model 3's robust bandwidth selections are from 9 to 15, as shown in Figure B.3. Lastly, for Model 4 (Figure B.4), the bandwidths range from 13 to 25 for robust estimates.

In addition to this approach to bandwidth selection sensitivity, we also present the results of an analysis of bandwidth selection method for each one of the models. Here, we present the estimates and 95% CI for ten different bandwidth selection methods. We find that our results are robust to the bandwidth selection method used.

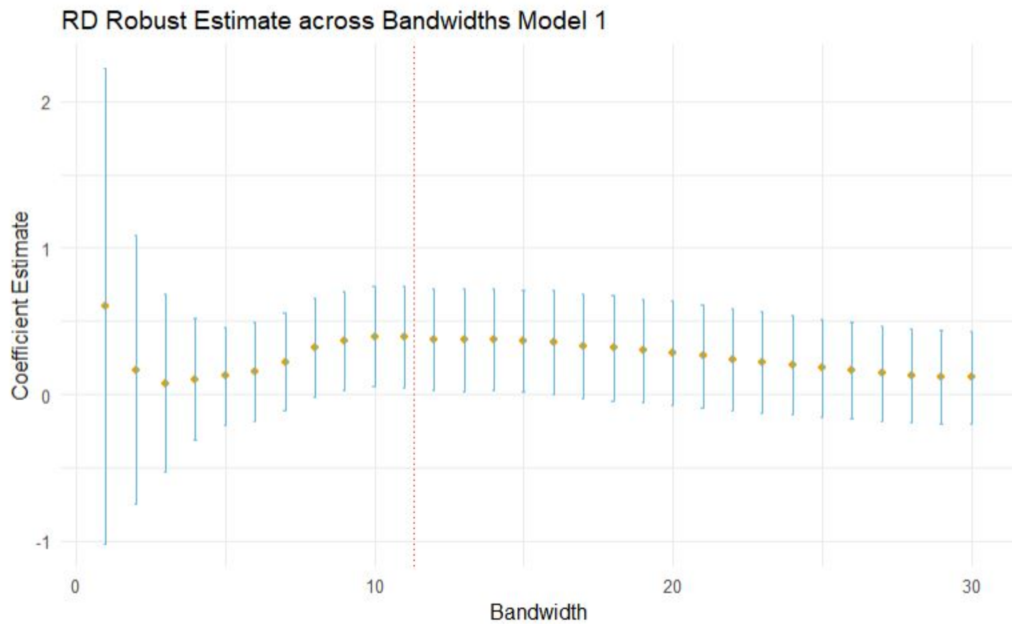

Figure B.1: Sensitivity to bandwidth selection for Model 1. Coefficient plot of Robust Estimates (in Log USD +1) and corresponding 95% CI for bandwidth values from 1 to 30. The red dotted line shows the optimal bandwidth selected in the main model presented in the main text

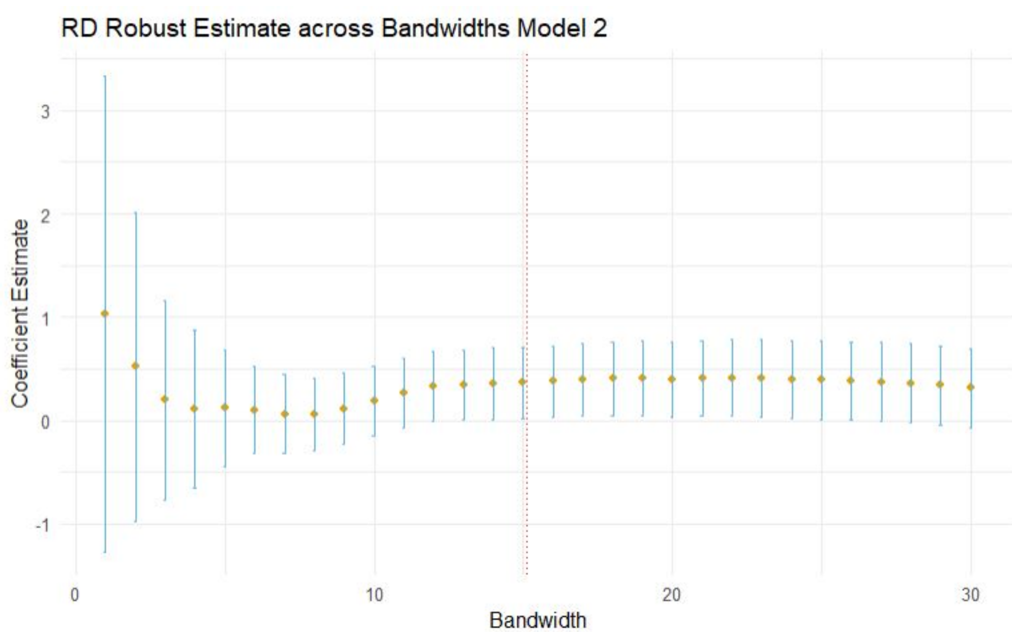

Figure B.2: Sensitivity to bandwidth selection for Model 2. Coefficient plot of Robust Estimates (in Log USD +1) and corresponding 95% CI for bandwidth values from 1 to 30. The red dotted line shows the optimal bandwidth selected in the main model presented in the main text

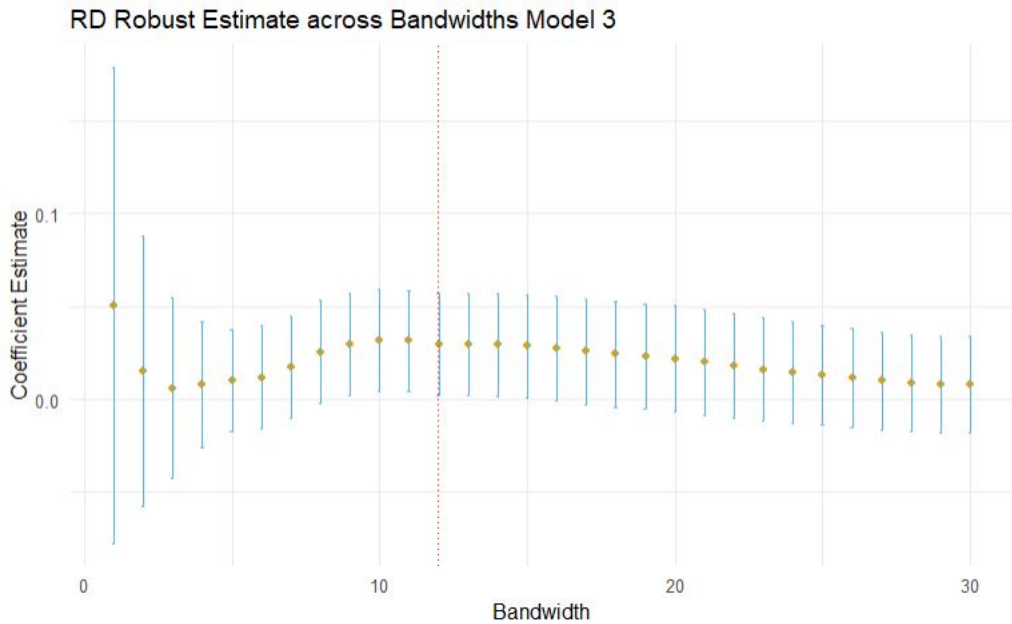

Figure B.3: Sensitivity to bandwidth selection for Model 3. Coefficient plot of Robust Estimates (in Log USD +1) and corresponding 95% CI for bandwidth values from 1 to 30. The red dotted line shows the optimal bandwidth selected in the main model presented in the main text

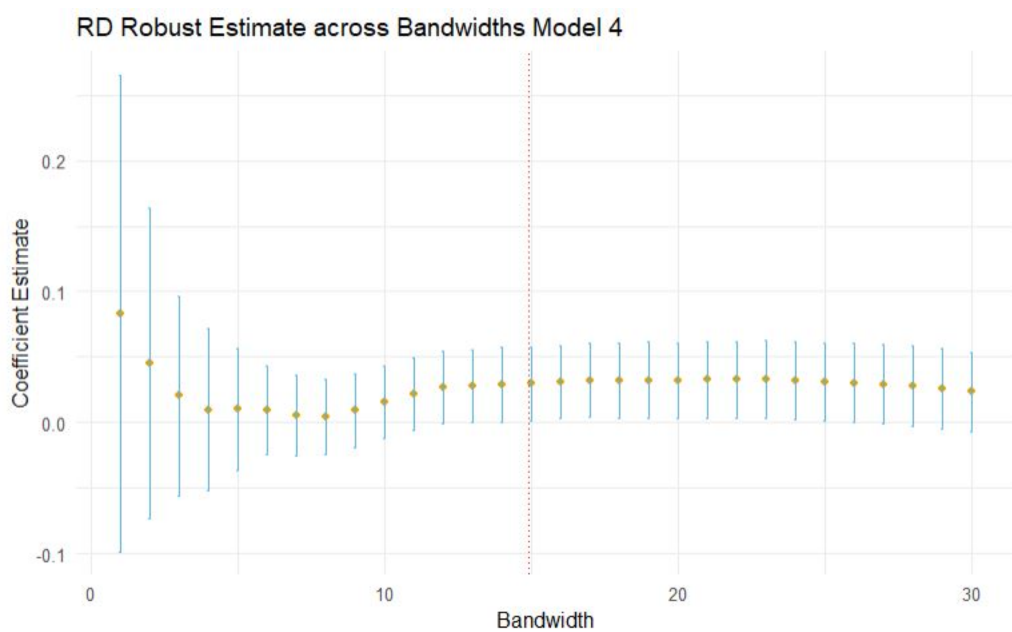

Figure B.4: Sensitivity to bandwidth selection for Model 4. Coefficient plot of Robust Estimates (in Log USD +1) and corresponding 95% CI for bandwidth values from 1 to 30. The red dotted line shows the optimal bandwidth selected in the main model presented in the main text

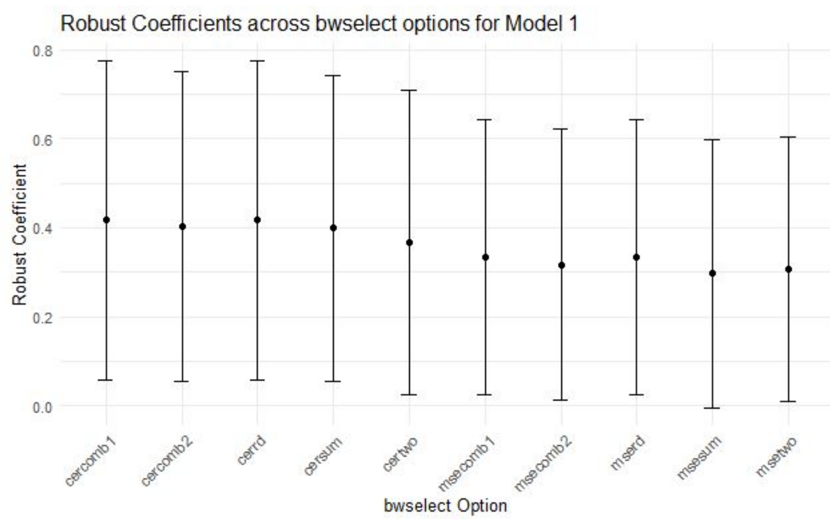

Figure B.5: Sensitivity to bandwidth selection method for Model 1

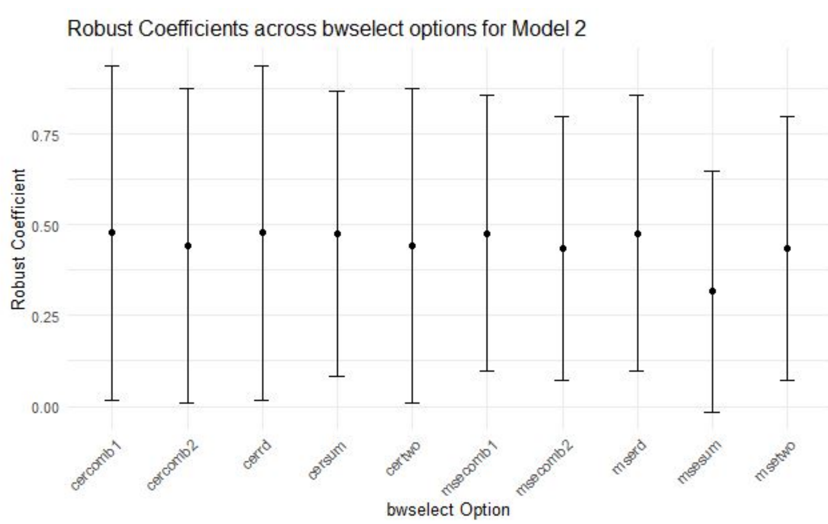

Figure B.6: Sensitivity to bandwidth selection method for Model 2

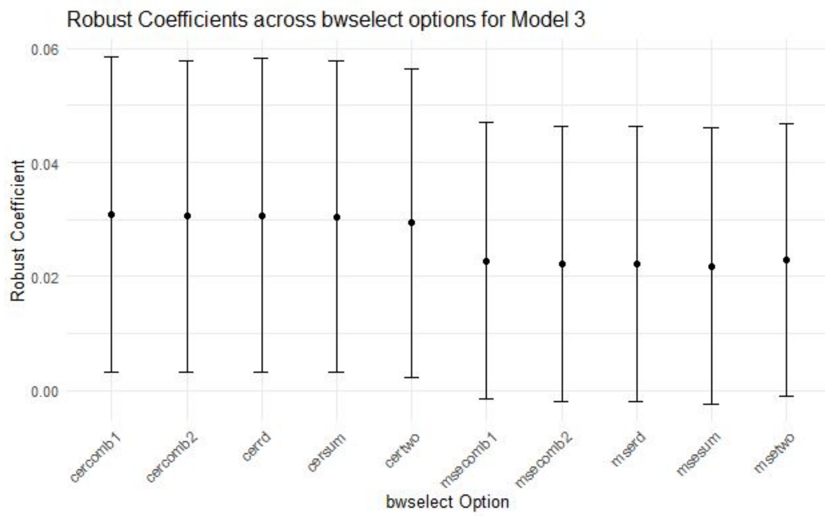

Figure B.7: Sensitivity to bandwidth selection method for Model 3

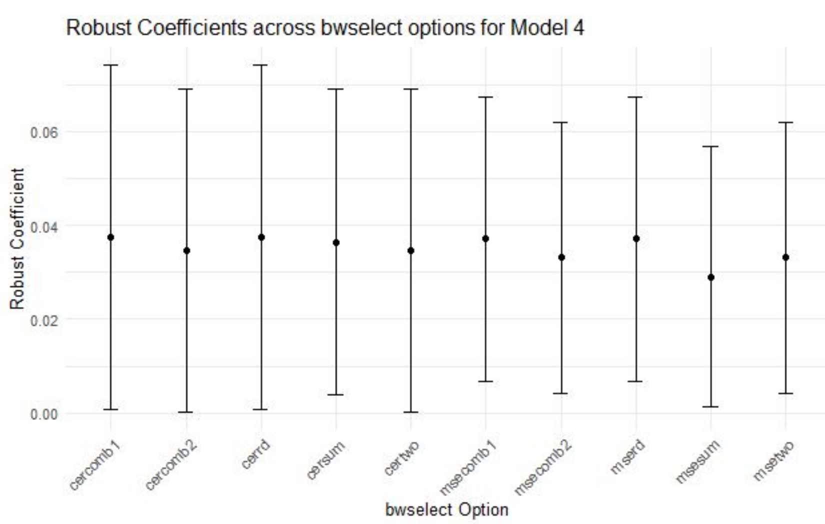

Figure B.8: Sensitivity to bandwidth selection method for Model 4

B.5 Continuity of covariates

In this section, we examine the continuity of the three covariates used in the models—adaptive capacity, sensitivity, and exposure—by plotting them against voting margins. This analysis aims to identify any variations in covariate values on different sides of the cutoff. Figures B.9, B.10, and B.11 suggest consistent continuity across these covariates with no apparent discrepancies at the cutoff.

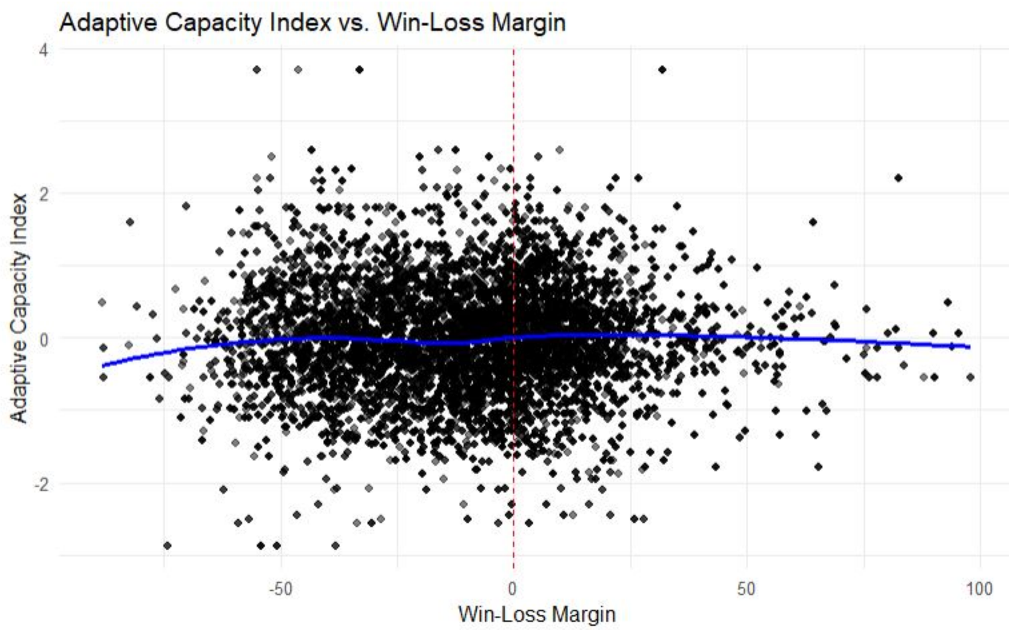

Figure B.9: Distribution of Adaptive Capacity Index values against voting margins, showing no apparent variation with voting margin.

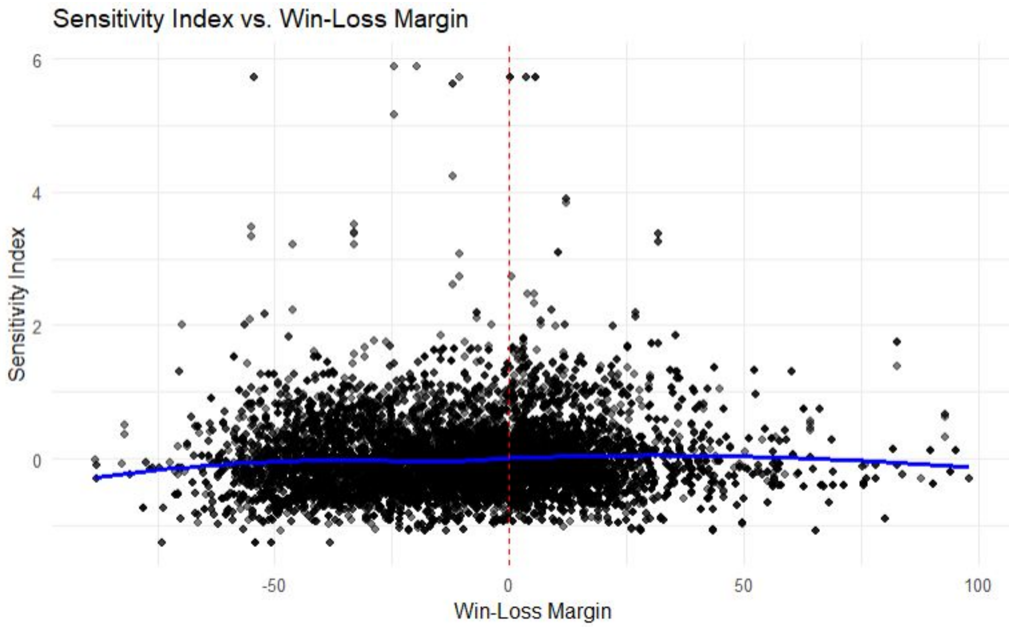

Figure B.10: Distribution of Sensitivity Index values against voting margins, indicating no discernible pattern that suggests variation with voting margin.

B.6 McCrary density test

We used the McCrary density test to check for potential discontinuities in the running variable, win-loss margin, around the zero cut point. We did not find any significant differences around the cut-off point (Figure B.12), suggesting no evidence of manipulation or irregularities in the distribution of the running variable at this threshold.

B.7 Sensitivity to threshold in vulnerability index

For the analysis of the distortionary effects of fund distribution based on alignment, we used a threshold of 75% in the vulnerability index. Municipality-years ranked in the top 25th percentile and above were considered vulnerable, while those below this threshold were considered not vulnerable. Below, we present results under two additional thresholds: one where ”vulnerable” is assigned to municipality-years above the 10th percentile, and another where

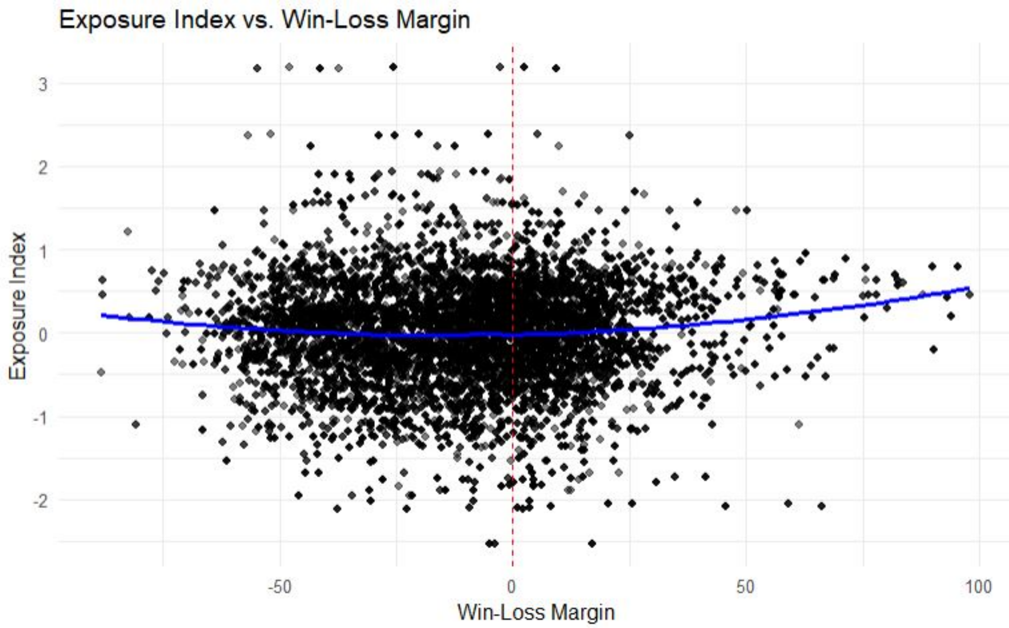

Figure B.11: Distribution of Exposure Index values against voting margins, with no visible patterns indicating variation with voting margin

”vulnerable” is assigned to municipality-years above the 50th percentile.

Vulnerability threshold at 10%

We find that not vulnerable yet politically aligned municipalities received an average of $27,191.87 per year, in contrast to the $18,111.32 their unaligned counterparts receive (Table B.27). This pattern extends to the likelihood of receiving both at least one project in any given year and the likelihood of receiving the maximum number of projects in any given year (Table B.28). We find that not vulnerable yet politically aligned municipalities have a probability of 0.049 of being awarded at least one project in a given year compared to a probability of 0.042 for their unaligned counterparts, and a probability of 0.012 of receiving 4 projects in a given year compared to the probability of 0.011 of their unaligned counterparts. These findings suggest a distortion in the allocation of funds where funds are diverted away from areas with higher need towards areas with lower need but that are aligned with the central government.

We estimate the magnitude of this distortion among municipalities considered not vulner-

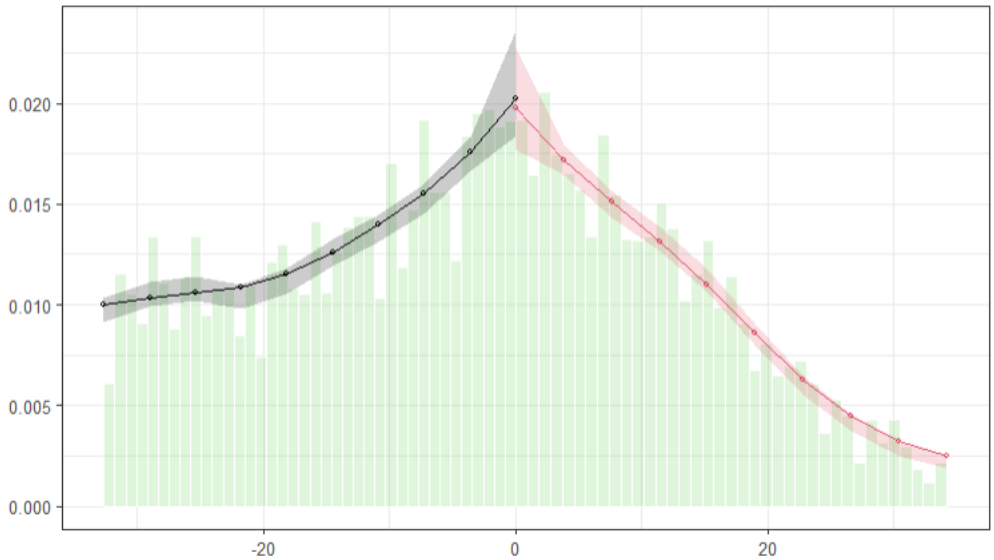

Figure B.12: McCrary density test suggesting no significant differences around the zero cut-off point for the running variable win-loss margin

able using a regression discontinuity design. The specifications are similar to those used in the main models, with the only difference being that the sample is restricted to municipalities below the top 90th percentile in the composite vulnerability index. When the threshold is set at the 90th percentile, we find that among the non-vulnerable, alignment is associated with receiving between 41.20% and 62.42% more funds in current USD (Table B.29) and between 0.03 and 0.04 more projects in project counts (Table B.30).

	Aligned	**Not Aligned**
Vulnerable		
Total for group	18 492 266.00	36 948 980.00
Observations	544	739
Average per observation	33 993.14	49 998.62
Not Vulnerable		
Total for group	119 752 998.00	133 136 302.00
Observations	4404	7351
Average per observation	27 191.87	18 111.32

Table B.27: Comparison of allocations in USD to municipalities grouped into four groups: Aligned Vulnerable, Aligned Not Vulnerable, Not Aligned Vulnerable, and Not Aligned Not Vulnerable

Group	Probability of at least one project/year	Probability of max projects/year
Aligned Not Vulnerable	0.049	0.012
Not Aligned Not Vulnerable	0.042	0.011
Aligned Vulnerable	0.055	0.014
Not Aligned Vulnerable	0.073	0.019

Table B.28: Probabilities of project occurrences per year

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Bias-Corrected RD Estimate	0.345		0.485	
Std. Err.	0.158		0.194	
z	2.186		2.503	
P>|z|	0.029		0.012	
95% C.I.	[0.036 , 0.655]		[0.105 , 0.865]	
Number of Total Obs.	9791		9791	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Number of Obs.	6160	3631	6160	3631
Eff. Number of Obs.	1873	1753	2543	2317
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	11.470	11.470	16.422	16.422
BW bias (b)	23.155	23.155	28.375	28.375
rho (h/b)	0.495	0.495	0.579	0.579
Unique Obs.	2237	1165	2237	1165

Table B.29: Bias-corrected RD estimate for Models 1 and 2 using a subset of municipalities considered not vulnerable under a 90% threshold, where those in the top 10th percentile are deemed vulnerable.

	(Model 3)		**(Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Bias-Corrected RD Estimate	0.026		0.036	
Std. Err.	0.011		0.014	
z	2.304		2.523	
P>|z|	0.021		0.012	
95% C.I.	[0.004 , 0.048]		[0.008 , 0.066]	
Number of Total Obs.	11755		11755	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Number of Obs.	7349	4406	7349	4406
Eff. Number of Obs.	2496	2360	3121	2957
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	13.004	13.004	17.353	17.353
BW bias (b)	24.891	24.891	29.0606	29.060
rho (h/b)	0.522	0.522	0.597	0.597
Unique Obs.	2658	1403	2658	1403

Table B.30: Bias Corrected RD Estimate for models 3 and 4 using a subset of municipalities considered not vulnerable under a 90% threshold, where those in the top 10th percentile are deemed vulnerable.

Vulnerability threshold at 50%

We find that not vulnerable yet politically aligned municipalities received an average of $32,444.29 per year, in contrast to the $16,142.82 their unaligned counterparts receive (Table B.31). This pattern extends to the likelihood of receiving both at least one project in any given year and the likelihood of receiving the maximum number of projects in any given year (Table B.32). We find that not vulnerable yet politically aligned municipalities have a probability of 0.052 of being awarded at least one project in a given year compared to a probability of 0.042 for their unaligned counterparts, and a probability of 0.013 of receiving 4 projects in a given year compared to the probability of 0.011 of their unaligned counterparts. These findings suggest a distortion in the allocation of funds where funds are diverted away from areas with higher need towards areas with lower need but that are aligned with the central government.

	Aligned	**Not Aligned**
Vulnerable		
Total for group	62 260 734.00	102 333 864.00
Observations	2606	3893
Average per observation	23 891.30	26 286.63
Not Vulnerable		
Total for group	75 984 530.00	67 751 418.00
Observations	2342	4197
Average per observation	32 444.29	16 142.82

Table B.31: Comparison of allocations in USD to municipalities grouped into four groups: Aligned Vulnerable, Aligned Not Vulnerable, Not Aligned Vulnerable, and Not Aligned Not Vulnerable

Group	Probability of at least one project/year	Probability of max projects/year
Aligned Not Vulnerable	0.052	0.013
Not Aligned Not Vulnerable	0.042	0.011
Aligned Vulnerable	0.047	0.012
Not Aligned Vulnerable	0.047	0.012

Table B.32: Probabilities of project occurrences per year

We estimate the magnitude of this distortion among municipalities considered not vulnerable using a regression discontinuity design. The specifications are similar to those used in the main models, with the only difference being that the sample is restricted to municipalities below the top 50th percentile in the composite vulnerability index. When the threshold is set at the 50th percentile, we find that among the non-vulnerable, alignment is associated with receiving between 18.53% and 32.58% more funds in current USD (Table B.33) and between 0.01 and 0.02 more projects in project counts (Table B.34), however, these results are not statistically significant at conventional levels.

	(Model 1)		**(Model 2)**	
Dependent Var.:	Log(Total USD+1)		Log(Total USD+1)	
Bias-Corrected RD Estimate	0.170		0.282	
Std. Err.	0.176		0.223	
z	0.966		1.265	
P>|z|	0.334		0.206	
95% C.I.	[-0.175, 0.515]		[-0.155, 0.720]	
Number of Total Obs.	6539		6539	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Number of Obs.	4197	2342	4197	2342
Eff. Number of Obs.	1441	1273	1849	1630
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	13.042	13.042	17.697	17.697
BW bias (b)	24.135	24.135	28.431	28.431
rho (h/b)	0.540	0.540	0.622	0.622
Unique Obs.	1514	769	1514	769

Table B.33: Bias-corrected RD estimate for Models 1 and 2 using a subset of municipalities considered not vulnerable under a 50% threshold, where those in the top 50th percentile are deemed vulnerable.

	(Model 3)		**(Model 4)**	
Dependent Var.:	Project Counts		Project Counts	
Bias-Corrected RD Estimate	0.014		0.023	
Std. Err.	0.014		0.018	
z	0.993		1.301	
P>|z|	0.321		0.193	
95% C.I.	[-0.014, 0.042]		[-0.012, 0.058]	
Number of Total Obs.	6539		6539	
BW type	mserd		mserd	
Kernel	Triangular		Triangular	
VCE method	NN		NN	
Number of Obs.	4197	2342	4197	2342
Eff. Number of Obs.	1433	1273	1820	1618
Order est. (p)	1	1	2	2
Order bias (q)	2	2	3	3
BW est. (h)	12.990	12.990	17.419	17.419
BW bias (b)	24.191	24.191	28.039	28.039
rho (h/b)	0.537	0.537	0.621	0.621
Unique Obs.	1514	769	1514	769

Table B.34: Bias Corrected RD Estimate for models 3 and 4 using a subset of municipalities considered not vulnerable under a 50% threshold, where those in the top 50th percentile are deemed vulnerable.

Appendix C

Supplemental Information for Chapter 3 - Empirical Insights into Hurricane Resilience Building: Testing Predictions and Evaluating Mitigation Strategies

C.1 Covariate Matching for HMP analysis

In this section, we describe the matching process for the HMP analysis and provide results for alternative definitions of treatment as well as different HMP adoption lags. We started with 1,061 places, which, when combined with specific hurricane events, resulted in 1,212 place-hurricane observations from 2014 to 2023. We began with 17 separate hurricane events and conducted a stratified matching process where each event was matched separately. The matching process considered five covariates: distance to the coast, population, median income, percentage of the population deemed poor, presence of local government (as indicated in the Census of Governments dataset), and the total number of hurricanes before the first hit within the study period.

In the main document, we define treated units as places that have maintained a HMP for five consecutive years prior to their hurricane exposure. Control units are those that have not had any HMP coverage for the five years leading up to the hurricane. The five-year period was chosen because HMPs are designed to last five years before they expire.

In this section we present results for an alternative definition of control units. In this specification, treated units still have continuous HMP coverage, but control units include a mix of those with partial HMP coverage and those with no coverage at all. We refer to this specification as "non-exclusionary control" to differentiate it from the main specification, which only includes control units without any HMP coverage before the hurricane. We also present results for multiple lag years of HMP adoption prior to hurricane impact, ranging from six to two years before the event. We do this for both control definitions.

We find consistency across the different time lags and definitions of treatment and control, with no significant effect of HMP adoption on outcomes related to hurricane impact and recovery.

Continuous coverage non exclusionary

Treatment: HMP 2 years prior

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Control: 133; Treated: 646

Total hurricane events (cohorts) included in analysis: 14

Treatment: HMP 3 years prior

In this model, we used a genetic matching algorithm with replacement.

Table C.1: Covariate Balance for treatment "HMP 2 years prior" with non-exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.865	0.655	1.487	0.513
Distance to coast (m)	26656.183	29202.271	-0.078	0.784
Population	11766.699	12228.048	-0.015	0.823
Med income	43989.020	54114.689	-0.348	1.081
Deemed poor %	30.490	21.725	0.410	1.724
CoG status	0.451	0.128	0.649	.
Total prior hurricanes	0.500	0.459	0.049	1.875

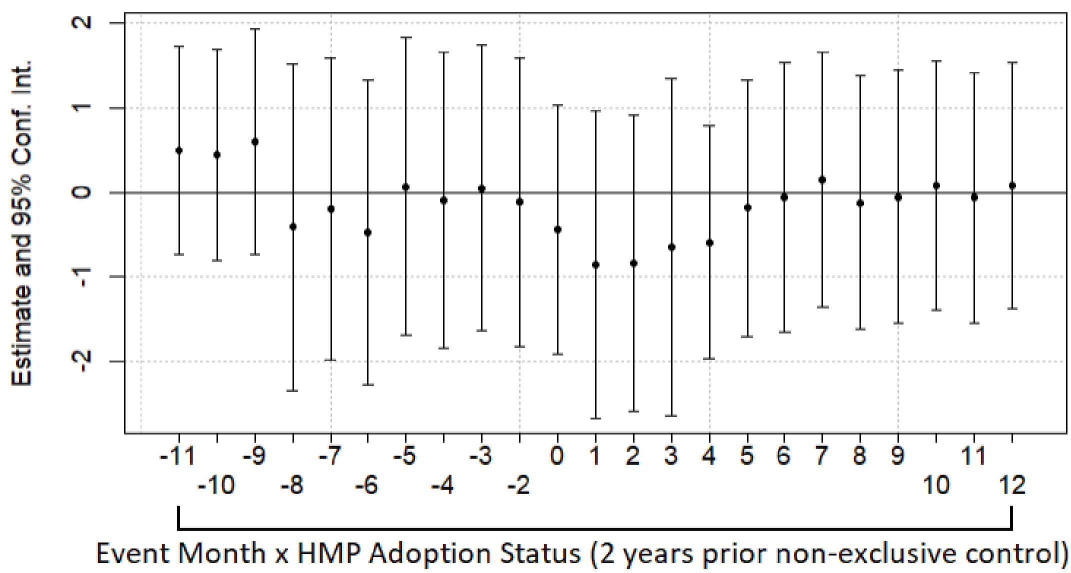

Figure C.1: Comparison in decline of illumination in places with and without HMP continuous coverage for 2 years prior to the time of hurricane.

Sample Size:

Control: 184; Treated: 538

Total hurricane events (cohorts) included in analysis: 14

Treatment: HMP 4 years prior

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Table C.2: Covariate Balance for treatment ”HMP 3 years prior” with non- exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.778	0.650	0.887	0.981
Distance to coast (m)	28781.471	22321.079	0.190	1.668
Population	12942.180	9299.186	0.108	3.296
Med income	46668.778	45916.656	0.025	1.110
Deemed poor %	28.434	29.084	-0.031	0.971
CoG status	0.483	0.147	0.673	.
Total prior hurricanes	0.520	0.440	0.090	1.778

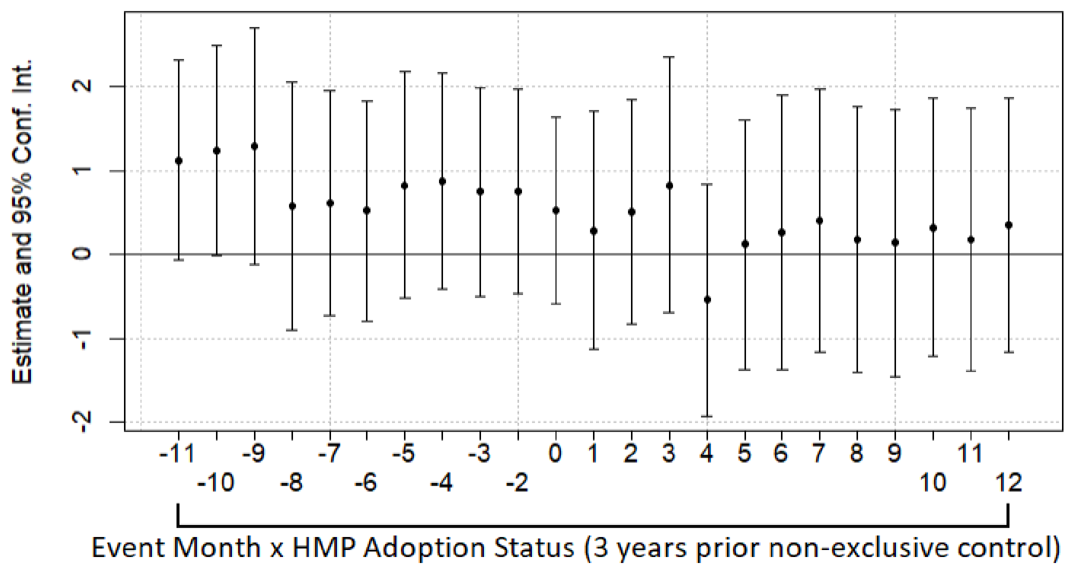

Figure C.2: Comparison in decline of illumination in places with and without HMP continuous coverage for 3 years prior to the time of hurricane.

Control: 184; Treated: 538

Total hurricane events (cohorts) included in analysis: 14

Treatment: HMP 5 years prior

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Control: 184; Treated: 538

Table C.3: Covariate Balance for treatment "HMP 4 years prior" with non- exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.778	0.650	0.887	0.981
Distance to coast (m)	28781.471	22321.079	0.190	1.668
Population	12942.180	9299.186	0.108	3.296
Med income	46668.778	45916.656	0.025	1.110
Deemed poor %	28.434	29.084	-0.031	0.971
CoG status	0.483	0.147	0.673	.
Total prior hurricanes	0.520	0.440	0.090	1.778

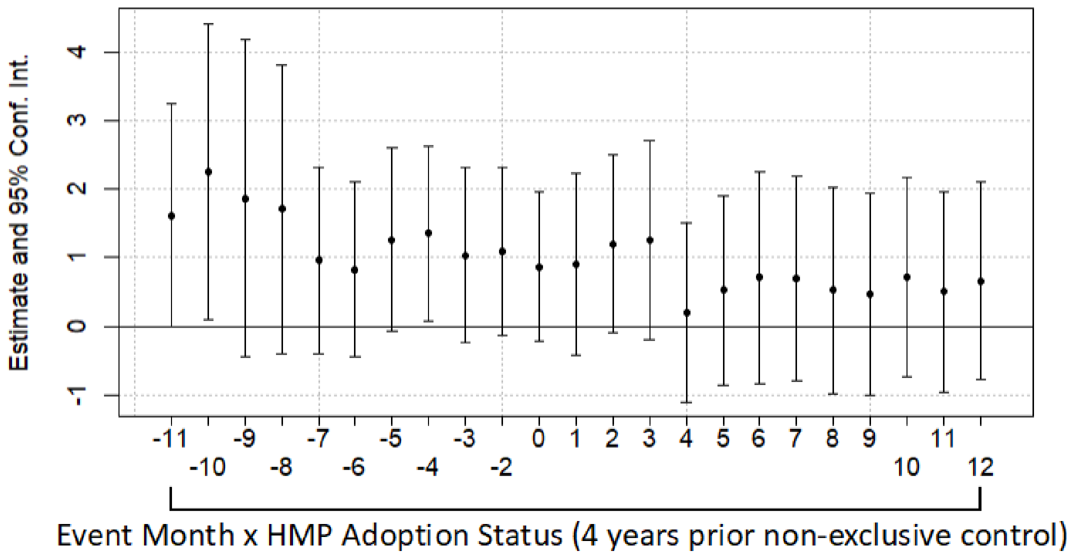

Figure C.3: Comparison in decline of illumination in places with and without HMP continuous coverage for 4 years prior to the time of hurricane.

Total hurricane events (cohorts) included in analysis: 14

Treatment: HMP 6 years prior

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Control: 184; Treated: 538

Total hurricane events (cohorts) included in analysis: 14

Table C.4: Covariate Balance for treatment ”HMP 5 years prior” with non- exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.778	0.650	0.887	0.981
Distance to coast (m)	28781.471	22321.079	0.190	1.668
Population	12942.180	9299.186	0.108	3.296
Med income	46668.778	45916.656	0.025	1.110
Deemed poor %	28.434	29.084	-0.031	0.971
CoG status	0.483	0.147	0.673	.
Total prior hurricanes	0.520	0.440	0.090	1.778

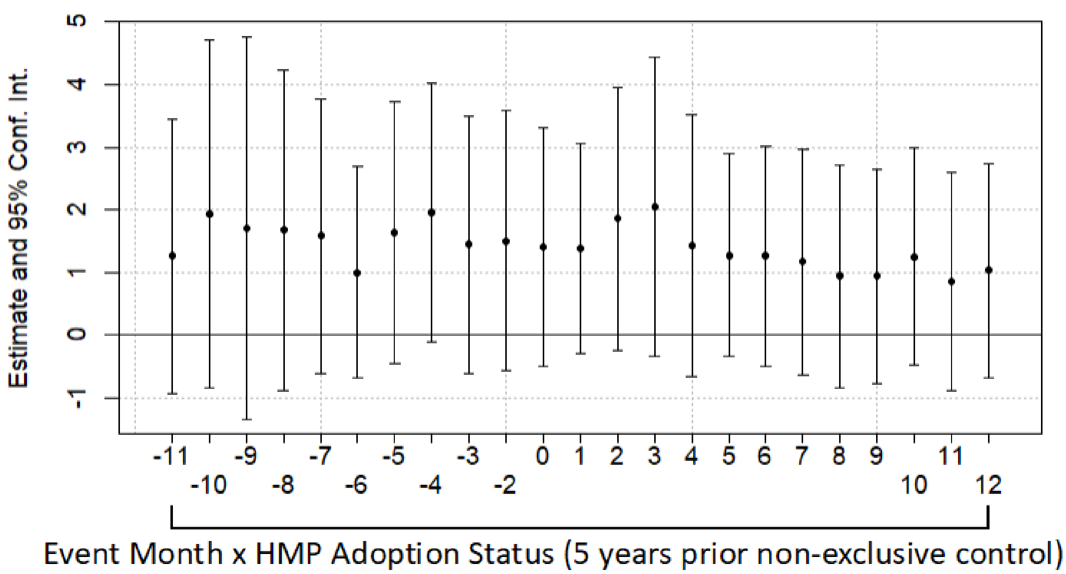

Figure C.4: Comparison in decline of illumination in places with and without HMP continuous coverage for 5 years prior to the time of hurricane.

Continuous coverage exclusionary

Treatment: HMP 2 years prior with strict control

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Control: 142; Treated: 600

Total hurricane events (cohorts) included in analysis: 11

Table C.5: Covariate Balance for treatment "HMP 6 years prior" with non- exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.778	0.650	0.887	0.981
Distance to coast (m)	28781.471	22321.079	0.190	1.668
Population	12942.180	9299.186	0.108	3.296
Med income	46668.778	45916.656	0.025	1.110
Deemed poor %	28.434	29.084	-0.031	0.971
CoG status	0.483	0.147	0.673	.
Total prior hurricanes	0.520	0.440	0.090	1.778

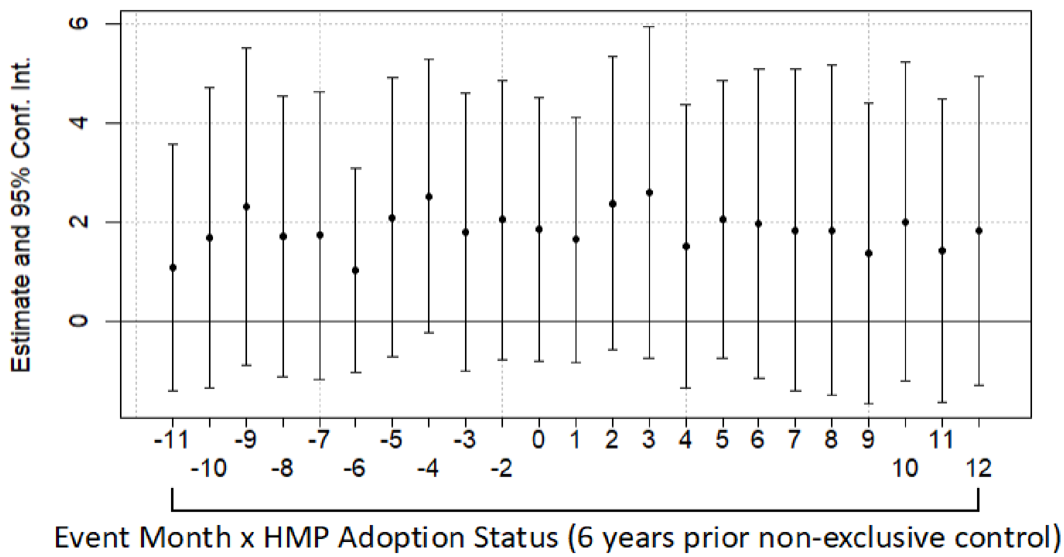

Figure C.5: Comparison in decline of illumination in places with and without HMP continuous coverage for 6 years prior to the time of hurricane.

Treatment: HMP 3 years prior with strict control

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Control: 116; Treated: 469

Total hurricane events (cohorts) included in analysis: 9

Table C.6: Covariate Balance for treatment "HMP 2 years prior" with exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.870	0.548	1.833	0.626
Distance to coast (m)	27194.777	31409.705	-0.127	0.699
Population	11712.545	11060.500	0.022	1.629
Med income	43258.252	57175.522	-0.480	0.895
Deemed poor %	31.345	19.196	0.567	2.195
CoG status	0.442	0.070	0.748	.
Total prior hurricanes	0.505	0.563	-0.068	1.427

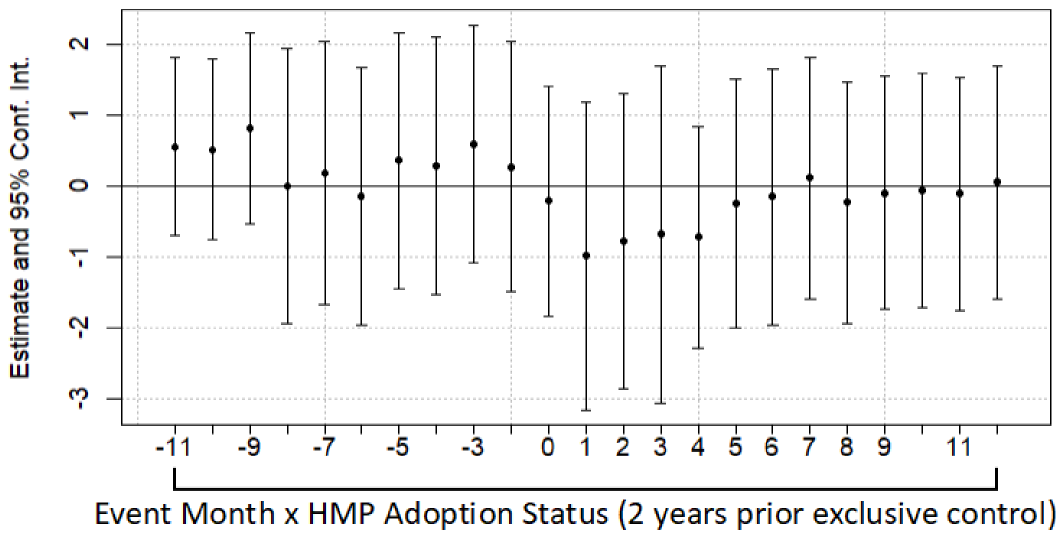

Figure C.6: Comparison in decline of illumination in places with and without HMP continuous coverage for 2 years prior to the time of hurricane.

Treatment: HMP 4 years prior with strict control

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Control: 116; Treated: 417

Total hurricane events (cohorts) included in analysis: 8

Table C.7: Covariate Balance for treatment "HMP 3 years prior" with exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.884	0.470	2.436	0.394
Distance to coast (m)	30151.319	21789.533	0.240	1.932
Population	12825.323	12646.691	0.006	1.682
Med income	46611.543	62484.087	-0.527	0.914
Deemed poor %	28.944	16.630	0.582	2.332
CoG status	0.476	0.035	0.883	.
Total prior hurricanes	0.518	0.509	0.011	1.901

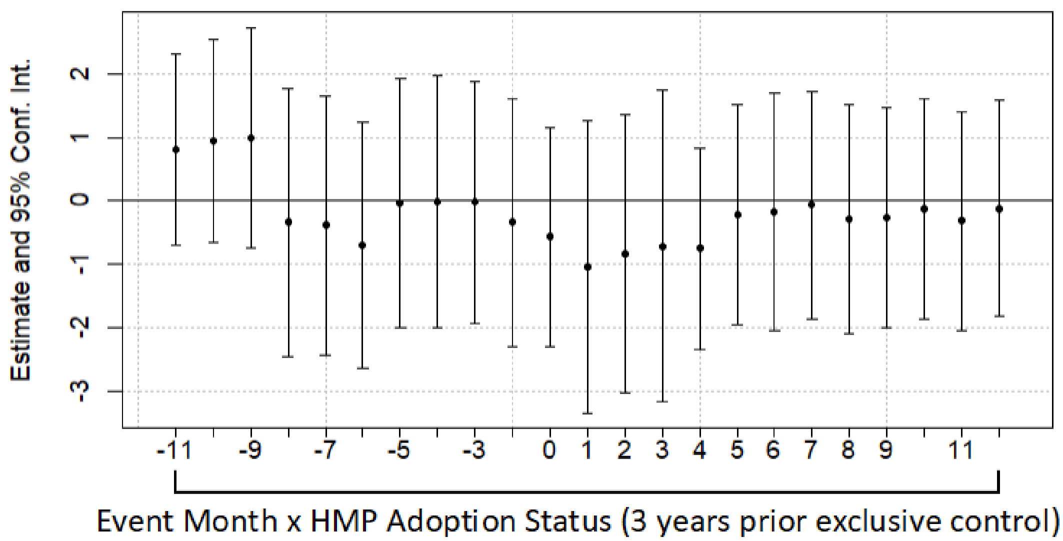

Figure C.7: Comparison in decline of illumination in places with and without HMP continuous coverage for 3 years prior to the time of hurricane.

Treatment: HMP 5 years prior with strict control

In this model, we used a genetic matching algorithm with replacement.

Sample Size:

Control: 105; Treated: 353

Total hurricane events (cohorts) included in analysis: 9

Treatment: HMP 6 years prior with strict control

In this model, we used a genetic matching algorithm with replacement.

Table C.8: Covariate Balance for treatment "HMP 4 years prior" with exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.873	0.458	2.279	0.490
Distance to coast (m)	32366.340	23499.664	0.248	1.836
Population	13748.392	10575.313	0.095	2.238
Med income	50108.317	63299.482	-0.439	0.838
Deemed poor %	26.295	16.722	0.468	2.132
CoG status	0.532	0.035	0.998	.
Total prior hurricanes	0.583	0.474	0.116	2.053

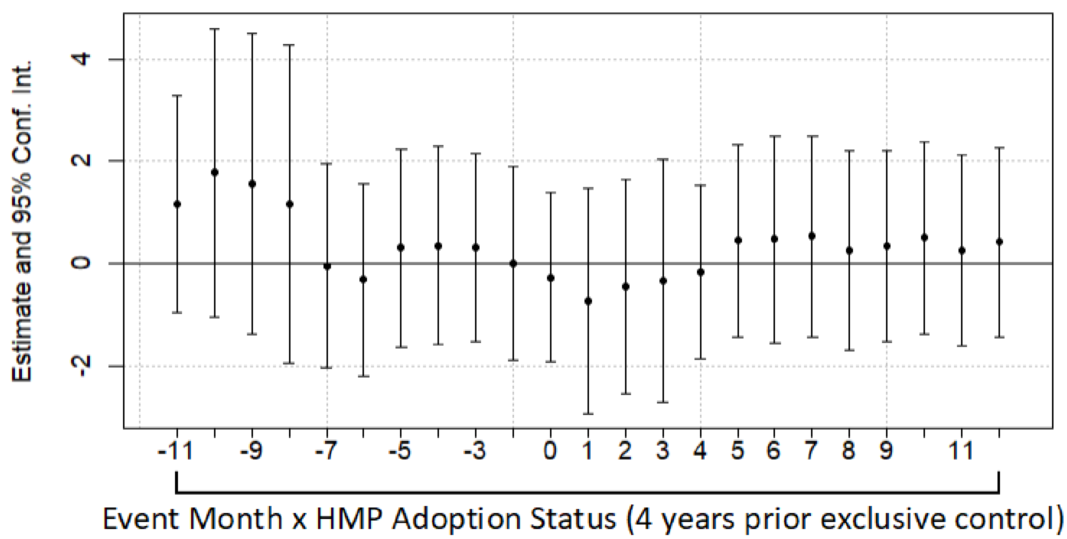

Figure C.8: Comparison in decline of illumination in places with and without HMP continuous coverage for 4 years prior to the time of hurricane.

Sample Size:

Control: 87; Treated: 264

Total hurricane events (cohorts) included in analysis: 9

Table C.9: Covariate Balance for treatment "HMP 5 years prior" with exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.881	0.402	2.398	0.768
Distance to coast (m)	34006.047	28587.587	0.148	1.574
Population	13743.705	10086.695	0.110	2.932
Med income	52035.392	60730.118	-0.297	0.794
Deemed poor %	24.794	17.377	0.371	2.015
CoG status	0.595	0.019	1.173	.
Total prior hurricanes	0.660	0.552	0.110	1.982

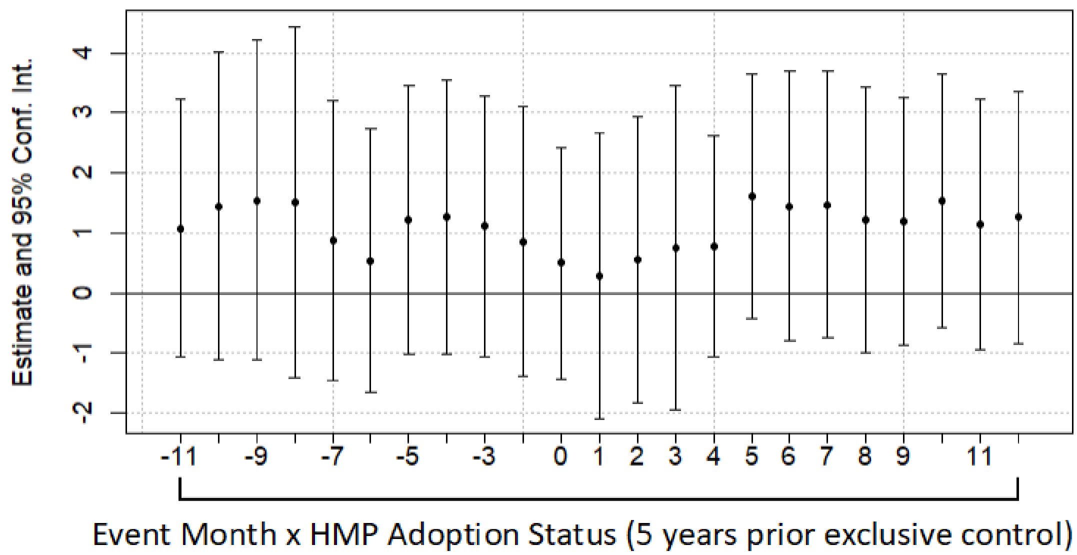

Figure C.9: Comparison in decline of illumination in places with and without HMP continuous coverage for 5 years prior to the time of hurricane.

Table C.10: Covariate Balance for treatment "HMP 6 years prior" with exclusionary control using genetic matching with replacement

Variable	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.876	0.377	2.336	1.020
Distance to coast (m)	38769.797	29329.905	0.250	1.717
Population	15004.886	11491.775	0.099	2.352
Med income	57798.418	61926.646	-0.157	1.054
Deemed poor %	19.419	15.864	0.217	1.585
CoG status	0.682	0.023	1.415	.
Total prior hurricanes	0.837	0.632	0.196	2.129

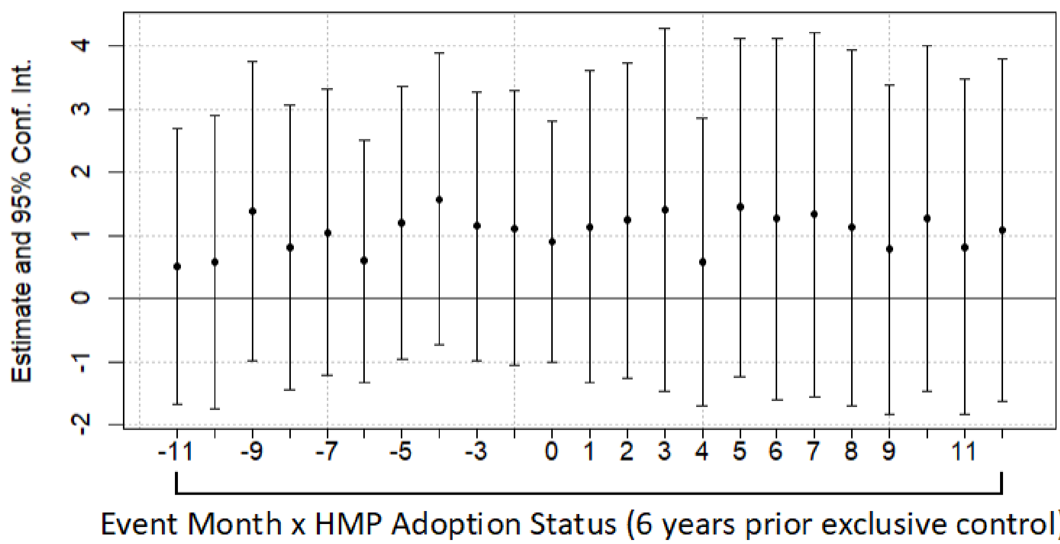

Figure C.10: Comparison in decline of illumination in places with and without HMP continuous coverage for 6 years prior to the time of hurricane.

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